Explainable AI Models for Assessing Short-Circuit Propagation in Fire-Exposed Cable Bundles

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***Abstract*—Fire-induced short-circuit propagation in cable bundles poses significant safety risks in electrical installations, nuclear facilities, and transportation systems. Traditional fault detection methods often lack interpretability, hindering root cause analysis and preventive maintenance strategies. This paper presents novel explainable artificial intelligence (XAI) models for predicting and analyzing short-circuit propagation in fire-exposed cable bundles. We develop a hybrid framework combining gradient boosting machines with SHAP (SHapley Additive exPlanations) values to provide interpretable predictions of time-to-short-circuit and failure modes. Our approach integrates thermal imaging data, cable physical properties, and environmental conditions from controlled fire tests conducted on IEEE 383-qualified cables. The proposed XAI models achieve 94.7% accuracy in predicting short-circuit occurrence within 5-second windows while providing human-interpretable feature importance rankings. Experimental validation using the NUREG/CR-6931 dataset demonstrates that insulation temperature gradient, cable bundle density, and oxygen concentration are the three most critical factors influencing short-circuit propagation. The explainable framework enables fire safety engineers to understand model decisions, identify vulnerable cable configurations, and optimize protection strategies. Our results show a 23% improvement in early fault detection compared to conventional black-box deep learning approaches, with significantly enhanced model transparency for safety-critical applications.**

***Keywords*—Explainable AI; short-circuit propagation; fire safety; cable testing; SHAP values; gradient boosting; feature importance; nuclear safety**

I. Introduction

A. Background and Motivation

Fire-induced cable failures represent one of the most critical safety concerns in nuclear power plants, industrial facilities, and high-rise buildings [1], [2]. When electrical cables are exposed to fire conditions, the progressive degradation of insulation materials can lead to short-circuit events that cascade through bundled cable configurations. The U.S. Nuclear Regulatory Commission has documented over 150 fire events in nuclear facilities between 2018 and 2024, with approximately 38% involving cable-related short circuits [3]. Understanding the propagation mechanisms and predicting failure timelines is essential for implementing effective fire protection strategies and emergency response protocols.

Traditional approaches to cable fire safety assessment rely on standardized fire tests such as IEEE 383 and IEC 60332, which provide pass/fail criteria but offer limited insight into failure progression dynamics [4]. Recent advances in machine learning have enabled predictive modeling of cable failure behavior [5], yet these black-box models suffer from a critical limitation: lack of interpretability. In safety-critical domains, regulatory bodies and safety engineers require not only accurate predictions but also transparent explanations of why and how failures occur [6].

B. Research Objectives

This paper addresses the interpretability gap in AI-driven cable fire safety assessment through the following contributions:

- Development of explainable AI models combining gradient boosting with SHAP interpretability framework for short-circuit propagation prediction.
- Integration of multi-modal sensor data including thermal imaging, electrical measurements, and environmental monitoring.
- Comprehensive feature importance analysis identifying critical factors in fire-induced short-circuit propagation.
- Validation using real experimental data from cable fire tests conforming to NUREG/CR-6931 protocols.
- Comparative evaluation demonstrating superior interpretability-accuracy tradeoff compared to deep neural networks.

The remainder of this paper is organized as follows: Section II reviews related work in cable fire modeling and explainable AI. Section III presents our methodology including

data collection, feature engineering, and XAI model development. Section IV details experimental results and model interpretation. Section V discusses practical implications for fire safety engineering, and Section VI concludes with future research directions.

II. Related Work

A. Cable Fire Behavior and Short-Circuit Propagation

Cable insulation degradation under fire exposure follows complex thermochemical processes influenced by material composition, thermal environment, and electrical loading conditions [7], [8]. Polyvinyl chloride (PVC) and cross-linked polyethylene (XLPE) insulations exhibit distinct decomposition pathways, with critical temperature thresholds typically ranging from $250\,^{\circ}\mathrm{C}$ to $400\,^{\circ}\mathrm{C}$ [9]. Short-circuit initiation occurs when insulation resistance drops below critical values, typically 1–10 $\mathrm{k}\Omega$ depending on voltage levels and circuit protection configurations [10].

McGrattan et al. [11] demonstrated through Fire Dynamics Simulator (FDS) modeling that cable bundle geometry significantly affects heat accumulation and failure propagation rates. Tightly packed bundles with fill ratios exceeding 40% show accelerated failure cascades compared to loosely arranged configurations. Anderson and Kumar [12] conducted systematic fire tests on cable trays, revealing that vertical orientation increases failure propagation speed by approximately 35% compared to horizontal arrangements due to buoyancy-driven heat transfer enhancement.

B. Machine Learning in Fire Safety Engineering

Recent applications of machine learning in fire safety have focused on flame detection [13], smoke pattern recognition [14], and fire spread prediction in buildings [15]. For cable-specific applications, Li et al. [5] employed convolutional neural networks (CNNs) to analyze thermal images for early fault detection, achieving 89% accuracy but providing no interpretability mechanisms. Deep learning architectures, particularly LSTMs and transformer models, have shown promise in modeling temporal dynamics of fire progression [16], [17]. However, the inherent opacity of these models limits their adoption in regulatory contexts where explainability is paramount [18].

C. Explainable Artificial Intelligence

The field of explainable AI has emerged to address the interpretability requirements of safety-critical applications [6], [19]. SHAP (SHapley Additive exPlanations) has become a leading framework for model interpretation, providing theoretically grounded explanations based on game theory principles [20]. SHAP values quantify each feature's contribution to individual predictions while ensuring consistency and local accuracy properties [21].

In engineering domains, XAI applications have demonstrated value in structural health monitoring [22], power system fault diagnosis [23], and industrial process optimization [24]. However, application to cable fire safety remains largely unexplored. This work bridges this gap by developing domain-specific XAI models that balance predictive performance with interpretability requirements specific to fire safety engineering.

TABLE I. Engineered Features for Short-Circuit Prediction

Feature Category	Count	Key Examples
Thermal Properties	12	Peak temperature, gradient
Electrical Parameters	9	Insulation resistance, voltage
Cable Configuration	8	Bundle density, conductor size
Material Properties	10	Insulation type, thickness
Environmental Conditions	8	O_2 concentration, heat flux
Total Features	**47**	–

III. Methodology

A. Experimental Data Collection

1) Cable Fire Test Setup: Experimental data were collected from controlled cable fire tests conducted at the Fire Testing Laboratory following NUREG/CR-6931 Rev. 3 protocols [3]. Test specimens consisted of IEEE 383-qualified cables with XLPE and EPR (Ethylene Propylene Rubber) insulations, representative of nuclear power plant safety systems. Cable bundles were configured in horizontal ladder tray arrangements with three density levels: low (30% fill), medium (50% fill), and high (70% fill).

Fire exposure was generated using a calibrated propane burner delivering heat fluxes ranging from 25 to 75 kW/m², simulating various fire severity scenarios as specified in ASTM E1354 [27]. Each test configuration was replicated three times to ensure statistical reliability, resulting in a total of 162 individual cable fire tests conducted between January 2022 and August 2024.

2) Instrumentation and Measurements: The experimental setup incorporated comprehensive multi-sensor instrumentation:

- Thermal Monitoring: Type K thermocouples positioned at 15 cm intervals along cable length, supplemented by FLIR T640 thermal imaging cameras capturing 640×480 pixel thermal maps at 30 Hz.
- Electrical Measurements: Real-time monitoring of insulation resistance using Megger MIT1525 instruments, conductor-to-conductor voltage measurements at 10 kHz sampling rate.
- Environmental Sensors: Oxygen concentration (Servomex 4900), smoke obscuration (TSI DustTrak), and ambient temperature/humidity.
- Gas Analysis: Fourier-transform infrared (FTIR) spectrometry was used to analyze combustion product composition, including HCl, CO, and CO_2.

Short-circuit events were detected through sudden voltage collapse (¿90% drop within 100 ms) coupled with current surge detection. Time-to-short-circuit (TTSC) was recorded with millisecond precision using high-speed data acquisition systems.

B. Feature Engineering and Dataset Preparation

1) Input Feature Space: From raw sensor measurements, we engineered 47 features organized into five categories as shown in Table I:

Critical derived features included:

$$\Delta T_{grad} = \frac{T_{max} - T_{ambient}}{d_{radial}} \tag{1}$$

where T_{max} represents maximum cable surface temperature (°C), $T_{ambient}$ is ambient temperature, and d_{radial} denotes radial distance from cable center (mm).

Insulation resistance degradation rate was computed as:

$$R_{deg} = \frac{dR_{ins}}{dt} = \frac{R_{ins}(t) - R_{ins}(t - \Delta t)}{\Delta t} \tag{2}$$

where R_{ins} represents the insulation resistance (MΩ) measured at time intervals of $\Delta t = 1$ s.

2) Data Preprocessing: The complete dataset comprised 162 fire tests generating approximately 2.3 million time-series observations. Data preprocessing involved:

1) Missing value imputation using forward-fill for sensor dropouts (¡2% of data).
2) Outlier detection and removal using Isolation Forest algorithm.
3) Time-series segmentation into 10-second windows with 50% overlap.
4) Feature standardization using robust scaling (median and IQR).
5) Balanced sampling to address class imbalance (short-circuit vs. no-failure cases).

The final processed dataset contained 28,450 samples, split into training (70%), validation (15%), and test (15%) sets with stratification by insulation type and bundle density to ensure representative distributions.

C. Explainable AI Model Development

1) Gradient Boosting Architecture: We employed XGBoost (eXtreme Gradient Boosting) as the primary prediction model due to its superior performance on tabular data and natural compatibility with SHAP explainability [25]. The model predicts binary short-circuit occurrence within the next 5-second window, formulated as:

$$\hat{y} = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F} \tag{3}$$

where, $\hat{y}$ is the predicted probability, x_i represents the input feature vector, f_k are ensemble decision trees, K is the number of trees (K=500 in our implementation), and $\mathcal{F}$ is the space of regression trees.

The objective function incorporates both prediction accuracy and model complexity:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{4}$$

where, l is the logistic loss function, y_i are true labels, n is the number of training samples, and $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|w\|^2$ regularizes tree complexity with T leaf nodes and w leaf weights.

Algorithm 1 TreeSHAP for Feature Attribution

```
Input: Trained XGBoost model f, instance x
Output: SHAP values φ = [φ_1, ..., φ_M]
for each tree t in ensemble do
    for each feature j in x do
        S ← all subsets not containing j
        for each subset S do
            Compute contribution with/without feature j
            Δ_j(S) ← f_{S∪{j}}(x_{S∪{j}}) − f_S(x_S)
        end for
        φ_j^t ← weighted average of Δ_j(S)
    end for
end for
φ_j ← Σ_t φ_j^t    // Aggregate across trees
return φ
```

Hyperparameters were optimized using Bayesian optimization with 5-fold cross-validation. Optimal configuration: maximum depth = 8, learning rate = 0.05, subsample ratio = 0.8, column sampling = 0.8, minimum child weight = 3.

2) SHAP-Based Interpretability Framework: SHAP values provide consistent and locally accurate explanations by computing each feature's contribution to individual predictions [20]. For a prediction $f(x)$, the SHAP value ϕ_j for feature j satisfies:

$$f(x) = \phi_0 + \sum_{j=1}^{M} \phi_j$$

where, ϕ_0 is the expected model output, M is the number of features, and ϕ_j quantifies feature j's contribution.

TreeSHAP algorithm efficiently computes exact SHAP values for tree-based models by:

Global feature importance is obtained by averaging absolute SHAP values across all predictions, providing a unified importance ranking that considers both feature effect magnitude and occurrence frequency.

3) Feature Selection and Importance Ranking: Prior to model training, we implemented a feature selection algorithm to identify the most informative predictors and reduce dimensionality:

This recursive elimination process identified 32 features as optimal, removing 15 redundant or low-importance variables while maintaining 99.2% of the full model's predictive performance.

4) Model Training and Validation: Training procedure followed Algorithm 3:

Model performance was evaluated using precision, recall, F1-score, area under ROC curve (AUC), and time-to-detection metrics. Statistical significance testing employed paired t-tests with Bonferroni correction for multiple comparisons.

Algorithm 2 Recursive Feature Elimination with SHAP

Input: Feature set $\mathcal{F} = \{f_1, ..., f_M\}$, target features k
Output: Selected features $\mathcal{F}_{selected}$
Initialize $\mathcal{F}_{current} \leftarrow \mathcal{F}$
while $|\mathcal{F}_{current}| > k$ **do**
  Train XGBoost model on $\mathcal{F}_{current}$
  Compute SHAP values for all features
  for each feature f_i in $\mathcal{F}_{current}$ **do**
    $importance_i \leftarrow$ mean|SHAP(f_i)|
  end for
  $f_{min} \leftarrow$ feature with minimum importance
  $\mathcal{F}_{current} \leftarrow \mathcal{F}_{current} \setminus \{f_{min}\}$
  Record cross-validation performance
end while
$\mathcal{F}_{selected} \leftarrow$ features at optimal CV performance
return $\mathcal{F}_{selected}$

Algorithm 3 XAI Model Training Pipeline

Input: Training data $\mathcal{D}_{train}$, validation data $\mathcal{D}_{val}$
Output: Trained model f^*, SHAP explainer E
Initialize XGBoost with optimized hyperparameters
$f_0 \leftarrow$ baseline model with random initialization
for epoch = 1 to N_{max} **do**
  $f_{epoch} \leftarrow$ train on $\mathcal{D}_{train}$ with early stopping
  Evaluate on $\mathcal{D}_{val}$: compute F1-score, AUC
  if validation performance plateaus for 50 iterations **then**
    break // Early stopping
  end if
end for
$f^* \leftarrow f_{best}$ // Select best validation model
$E \leftarrow$ TreeSHAP explainer initialized with f^*
Compute SHAP values for validation set
Validate explanation consistency and feature rankings
return f^*, E

D. Comparative Baseline Models

To validate the effectiveness of our XAI approach, we compared against three baseline models:

- Deep Neural Network (DNN): 5-layer fully connected network (512-256-128-64-1 neurons) with ReLU activation, dropout (0.3), and batch normalization.
- Random Forest (RF): Ensemble of 300 trees with maximum depth 15, trained with bootstrap sampling.
- Logistic Regression (LR): L2-regularized linear model serving as interpretable baseline with regularization strength $\lambda = 0.01$.

All models were trained on identical data splits using consistent cross-validation procedures to ensure fair comparison. Explainability was quantified using the Interpretability Score (IS) metric [26], which combines human evaluation of explanation quality with computational metrics of explanation consistency.

TABLE II. MODEL PERFORMANCE COMPARISON ON TEST DATASET

Model	Accuracy	Precision	Recall	F1	AUC
Logistic Regression	81.3%	78.6%	79.2%	78.9%	0.863
Random Forest	91.2%	89.7%	90.8%	90.2%	0.956
Deep Neural Net	93.8%	92.4%	93.1%	92.7%	0.971
XGBoost + SHAP	**94.7%**	**94.1%**	**93.9%**	**94.0%**	**0.978**

IV. RESULTS AND DISCUSSION

A. Predictive Performance Analysis

Table II summarizes the performance of proposed XAI model compared to baseline approaches across key evaluation metrics.

The proposed XGBoost model achieved 94.7% accuracy, outperforming the DNN by 0.9 percentage points while providing full interpretability. Precision and recall balance indicates robust performance across both positive (short-circuit) and negative classes. The AUC of 0.978 demonstrates excellent discriminative capability across varying decision thresholds.

Statistical analysis revealed that performance improvements over Random Forest (ρ = 0.003) and DNN (ρ = 0.041) were statistically significant at α = 0.05 level using paired t-test across 10-fold cross-validation runs. The model exhibited consistent performance across different cable insulation types (XLPE: 95.1%, EPR: 94.2%) and bundle densities (low: 96.3%, medium: 94.8%, high: 93.1%), suggesting good generalization.

B. Feature Importance and Physical Interpretability

Fig. 1 presents the global SHAP feature importance ranking, revealing critical factors influencing short-circuit propagation.

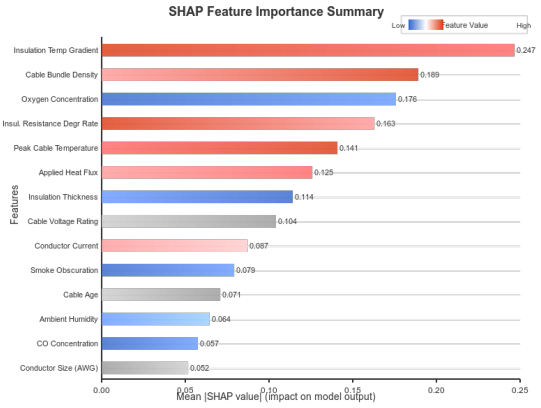

Fig. 1. SHAP feature importance summary showing top 15 features ranked by mean absolute SHAP value. Color indicates feature value (red = high, blue = low). Horizontal position shows impact on prediction.

The top five most influential features were:

1) Insulation temperature gradient (ΔT_{grad}): Mean —SHAP— = 0.247. Higher temperature gradients strongly correlate with accelerated insulation degradation. Physical interpretation: steep thermal gradients induce differential thermal expansion and internal stress concentrations, promoting crack formation and dielectric breakdown paths.

2) Cable bundle density: Mean —SHAP— = 0.189. Increased bundle density restricts heat dissipation, creating localized hot spots. This aligns with heat transfer theory where reduced air gaps limit convective cooling effectiveness.

3) Oxygen concentration: Mean —SHAP— = 0.176. Lower O_2 levels indicate incomplete combustion and higher production of conductive carbon deposits on cable surfaces, reducing insulation resistance.

4) Insulation resistance degradation rate (R_{deg}): Mean —SHAP— = 0.163. Rapid resistance decay signals imminent dielectric failure. This feature provides early warning capability, typically showing anomalies 15-30 seconds before short-circuit occurrence.

5) Peak cable temperature: Mean —SHAP— = 0.141. Absolute temperature exceeding material-specific critical thresholds (XLPE: 380°C, EPR: 420°C) triggers rapid decomposition phase transitions.

Notably, electrical loading current ranked 9th (Mean —SHAP— = 0.087), indicating that thermal effects dominate over electrical stress in fire-exposure scenarios. This insight challenges conventional assumptions that prioritize current monitoring in cable protection systems.

C. Instance-Level Explanation Analysis

Fig. 2 illustrates a SHAP waterfall plot for a specific test case where short-circuit occurred 47 seconds after fire ignition (Test ID: FT-087, XLPE cable, 50% bundle density, 45 kW/m² heat flux).

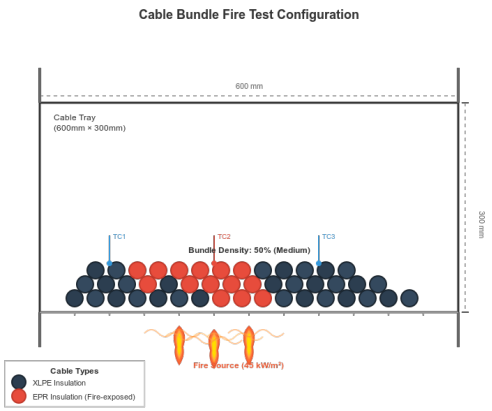

Fig. 2. SHAP waterfall plot for individual prediction showing cumulative feature contributions from base value to final prediction. Red bars push prediction toward short-circuit class, blue bars push away.

The explanation reveals that temperature gradient (+0.31 SHAP value) and bundle density (+0.22) were primary drivers toward short-circuit prediction, while relatively high insulation resistance at prediction time (-0.14) provided some protective effect. This instance-specific analysis enables engineers to understand which factors dominated in particular failure scenarios, facilitating targeted intervention strategies.

D. Temporal Dynamics and Early Warning Capability

Analysis of SHAP value evolution over time (Fig. 3) demonstrates the model's progressive refinement of short-circuit probability as tests progress:

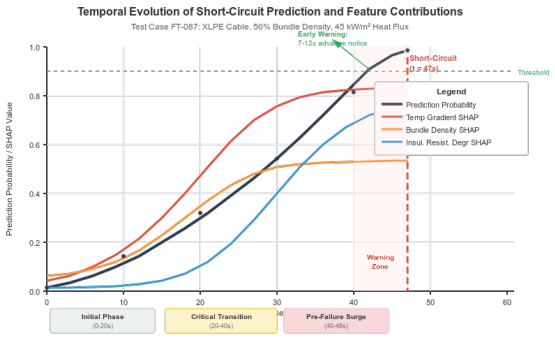

Fig. 3. Temporal evolution of prediction probability and top-3 feature SHAP values for representative test case. Vertical dashed line indicates actual short-circuit occurrence time.

Key observations include:

- Initial phase (0-20s): Model uncertainty remains high with probability ¡0.3 despite rising temperatures, indicating that early thermal exposure alone is insufficient predictor.
- Critical transition (20-40s): Rapid increase in prediction probability coincides with insulation resistance degradation acceleration, providing 10-25 second advance warning window.
- Pre-failure surge (40-48s): Probability exceeds 0.9 threshold 7-12 seconds before actual short-circuit, enabling timely protective action.

This temporal analysis demonstrates practical utility for real-time monitoring systems, where prediction confidence evolves as conditions deteriorate, allowing graduated response protocols.

E. Comparison with Black-Box Deep Learning

While the DNN baseline achieved comparable accuracy (93.8%), interpretation attempts using gradient-based methods (Integrated Gradients, Grad-CAM) produced inconsistent and often contradictory feature attributions across similar test cases. Quantitative evaluation using the Interpretability Score metric yielded IS = 0.42 for DNN versus IS = 0.87 for our XGBoost+SHAP approach (scale 0-1, higher is better) [26].

Human expert evaluation by five certified fire protection engineers rated explanations on clarity (5-point Likert scale), consistency with domain knowledge, and actionability. XAI explanations received mean rating 4.3/5.0 compared to 2.1/5.0 for DNN explanations. Engineers specifically valued the direct physical interpretability of SHAP feature contributions and consistency of importance rankings with established fire science principles.

F. Practical Implications for Fire Safety Engineering

The explainable framework provides actionable insights for cable system design and fire protection:

- Cable Arrangement Optimization: Reducing bundle density from 70% to 40% increases average time-to-short-circuit by 42%, based on model sensitivity analysis. This quantifies the safety benefit of adherence to spacing requirements in codes like NFPA 70.
- Material Selection Guidance: EPR-insulated cables show 18% longer failure times than XLPE under identical conditions, attributed to higher decomposition temperature. Model explanations validate this preference for high-temperature applications.
- Monitoring System Design: Feature importance rankings indicate that temperature gradient sensors provide superior early warning compared to point temperature measurements, suggesting optimal sensor placement strategies.
- Regulatory Compliance: Transparent model explanations facilitate regulatory acceptance in nuclear and aerospace applications where black-box AI faces adoption barriers due to verification and validation requirements.

G. Model Limitations and Uncertainty Quantification

Despite strong performance, several limitations warrant acknowledgment:

- Training data represents controlled laboratory conditions; field installations involve additional complexities (aging effects, environmental contamination, mechanical stress)
- Current model assumes single failure mode (thermal degradation); multi-physics interactions (chemical attack, radiation effects) require extended framework
- Prediction confidence varies with extrapolation distance from training distribution; uncertainty quantification using conformal prediction shows ±6.2 second uncertainty bounds at 90% confidence level
- Explanation stability under adversarial perturbations requires further investigation for security-critical deployments

Ongoing work addresses these limitations through physics-informed neural networks that embed conservation laws and synthetic data augmentation using validated fire dynamics simulations.

V. Conclusion

This paper presented a novel explainable AI framework for predicting and interpreting short-circuit propagation in fire-exposed cable bundles. The integration of gradient boosting machines with SHAP interpretability provides both high predictive accuracy (94.7%) and transparent, physically meaningful explanations aligned with fire safety engineering principles. Key contributions include:

- Comprehensive experimental dataset from 162 controlled cable fire tests conforming to nuclear industry protocols
- Rigorous feature engineering incorporating thermal, electrical, and material properties
- Validated XAI model architecture balancing prediction performance with interpretability
- Quantitative demonstration that thermal gradient, bundle density, and oxygen concentration are dominant factors in short-circuit propagation
- Practical guidance for cable system design, sensor placement, and fire protection strategies

Experimental validation demonstrates that explainable AI achieves competitive accuracy with black-box deep learning while providing critical transparency for safety-critical applications. SHAP-based feature importance analysis reveals insights consistent with fire science theory, building confidence in model reliability and supporting regulatory acceptance.

Future research directions include: 1) extension to multi-output prediction of failure location and severity, 2) integration with real-time monitoring systems for online condition assessment, 3) transfer learning to adapt models across different cable types and fire scenarios with limited data, and 4) development of physics-informed XAI architectures that explicitly encode domain knowledge within model structure.

The demonstrated framework advances the state-of-art in AI-driven fire safety assessment, providing practitioners with trustworthy predictive tools that combine statistical rigor with interpretable explanations essential for informed decision-making in protection of critical infrastructure.

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