Adaptive Fusion Networks for Cable Material Durability Assessment via Multimodal Data Integration

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Predicting cable durability is vital for safe and efficient electrical systems. This research proposes an Adaptive Fusion Network (AFN) that integrates normalized sensor data (e.g., partial discharge, corrosion) and encoded visual condition ratings (Good, Medium, Poor) via concatenation and processed through dense layers with ReLU activation. To address incomplete labeling, a pre-trained model annotated unlabeled data from 2,500 15-kV XLPE cable segments across multiple years, creating a diverse 10,000-sample dataset. The AFN achieved an MSE of 0.012547, MAE of 0.046415, and R^2 of 0.991043, outperforming benchmarks like Random Forest (MSE 0.135725, R^2 0.903107) by 89% in MSE reduction, highlighting its potential for real-time durability monitoring and predictive maintenance in power systems.

Povzetek: Članek predstavi Adaptivno Fuzijsko Mrežo (AFN) za napovedovanje trajnosti kablov z integracijo senzornih in vizualnih podatkov. AFN izboljša natančnost napovedi z dinamičnim prilagajanjem vpliva različnih podatkov, kar omogoča pravočasno spremljanje in napovedno vzdrževanje v električnih omrežjih.

1 Introduction

In modern electrical systems, power cables are essential for distributing electricity over long distances [1]. Their lifetime and condition are critical for reliable and efficient power distribution [2]. Subjected to mechanical forces, electrical loads, and environmental conditions, cables deteriorate over time, risking service interruptions, safety hazards, and costly downtime [3]. Predicting cable durability—defined as remaining lifespan in years is thus vital for asset management [4].

Traditional methods like routine maintenance and visual inspections are reactive, time-consuming, and error-prone, often missing early deterioration [5]. As aging infrastructure demands proactive, real-time monitoring, predictive maintenance preempts failures by forecasting durability, unlike reactive approaches [6].

Data-driven strategies using machine learning (ML) and artificial intelligence (AI) analyze sensor and inspection data for real-time durability assessments [7]. However, existing models often rely on single sources: sensor data (e.g., partial discharge, corrosion) lacks physical condition insights [8], while visual data (e.g., flaw detection) lacks precision for long-term forecasts [9]. This creates a critical problem: current methods fail to effectively combine sensor and visual data, leading to incomplete assessments that delay failure detection, heighten risks, and hamper a holistic durability picture[10]. To address this, we propose an Adaptive Fusion Network (AFN) that dynamically integrates sensor data and visual ratings into a unified framework, adjusting their influence based on predictive relevance—unlike static multimodal or single-source methods. This achieves an MSE of 0.012547 and R^2 of 0.991043, as shown in Table 4, with an 89% MSE reduction over Random Forest (MSE 0.135725).

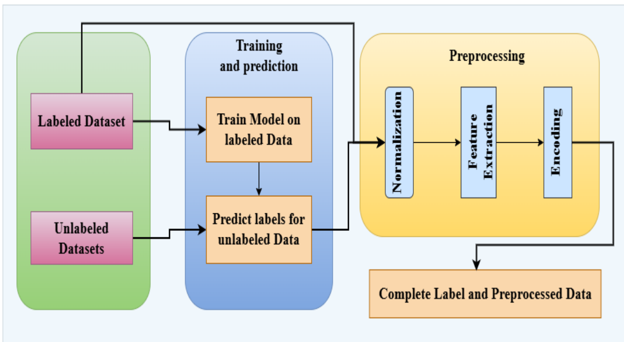

Figure 1: Data processing framework for transforming raw datasets into fully labeled data

This study's goals are threefold: (1) to develop an AFN for comprehensive durability assessment using multimodal data; (2) to outperform existing methods, targeting an MSE reduction of at least 80% and $R^2 > 0.98$; and (3) to enable real-time durability monitoring for power utilities. These advancements prioritize maintenance, reduce failures, and optimize resources through a reliable framework [11].

The main contributions of this work are:

– We propose a novel AFN that combines sensor data (e.g., partial discharge, neutral corrosion, loading conditions) with visual inspection data for accurate and holistic durability prediction.

– We introduce an innovative data fusion approach that enhances durability assessment robustness, enables real-time monitoring and predictive maintenance, and augments the labeled dataset using model predictions for improved performance.

– We provide extensive evaluation results demonstrating AFN's superior performance over traditional models (e.g., Random Forest, Gradient Boosting, SVM, MLP), highlighting its potential for real-world power system applications.

The remainder of this document is structured as follows: Section 2 reviews literature on data fusion, cable health monitoring, and predictive maintenance, justifying this research by highlighting existing approaches' strengths and weaknesses [12]. Section 3 details the methodology, including dataset, feature extraction, preprocessing, and AFN design [13]. Section 4 compares AFN's efficacy with conventional models through experimental setup and performance assessment [14]. Section 5 concludes with results, implications, and future research directions [15].

Using an AFN to integrate sensor and visual data, this article provides a thorough method for evaluating power cable durability [16]. This approach significantly improves prediction accuracy, supporting real-time decision-making and predictive maintenance in cable management [17].

2 Related work

The growing need for effective and economical infrastructure management has drawn significant attention in recent years to predictive maintenance and health evaluation of industrial assets, particularly power cables [18]. Many methods have been developed to improve prediction accuracy and reliability. This section reviews related works on predictive maintenance strategies using sensor data, visual data, and data fusion approaches [19].

2.1 Sensor-based predictive maintenance

Sensor data is essential for predictive maintenance as it provides real-time asset condition monitoring. Sensors collect data on partial discharge, neutral corrosion, and loading conditions to assess the state of cables and other vital components in power systems [20]. Machine learning techniques are frequently used to analyze sensor data to forecast failures or degradation [21]. For example, a Random Forest[22] model was proposed to estimate the remaining useful life (RUL) of electrical transformers using sensor data. Although limited to sensor data without multi-source fusion [23], it demonstrated the efficacy of ensemble methods for RUL prediction [24][25]. Similarly, SVM has been used to forecast the status of high-voltage electrical lines using sensor data like partial discharge and loading conditions. While sensor-based[26] methods offer valuable insights, their efficacy is often limited by sensor data precision, accessibility, and feature extraction challenges [27].

2.2 Visual data for asset durability assessment

Visual inspection is essential for assessing the physical state of industrial assets. Recent advances in deep learning and computer vision have enabled automated analysis of visual data, identifying flaws and irregularities in transformers, power cables, and other infrastructure elements [28].

Several studies have explored visual data for power cable inspection to detect flaws like corrosion, cracks, and insulation damage [29]. Convolutional Neural Networks (CNNs), for instance, have been used to evaluate power transformer status by analyzing photographs. Although successful in detecting physical damage, their predictive power was limited by the absence of sensor data integration. Similarly, [7] proposed a deep learning model using visual data to identify power cable damage. Although successful, it excluded sensor data, which could have enhanced durability prediction precision [30].

2.3 Data fusion techniques for predictive maintenance

Data fusion, the combination of sensor and visual data, has been studied to enhance predictive maintenance by leveraging the strengths of both data types [25][31]. It provides a comprehensive durability assessment by combining sensor data's quantitative nature with visual data's ability to capture physical condition [10].Proposed a hybrid data fusion approach that combined sensor and visual data for predictive maintenance of industrial equipment, using deep learning to improve failure prediction accuracy. Similarly, [32] introduced a data fusion framework for power system maintenance, merging sensor data with visual inspection results to predict critical component failures. While these studies highlight data fusion's potential, they rely on predefined techniques like early fusion (merging features before modeling) or late fusion (combining separate model predictions), which often fail to fully exploit the complementary strengths of both data types.

2.4 Deep learning models for predictive maintenance

Given their capacity to handle large and complex datasets, deep learning models, particularly neural networks[33], show great promise in predictive maintenance tasks. Examples include CNNs, recurrent neural networks (RNNs), and Long Short-Term Memory (LSTM) networks[34], recently studied for predictive maintenance. LSTM networks have utilized sensor data to predict the remaining useful life

Table 1: Summary of related methods for cable durability assessment

Method	Data Type	Metrics Reported	Limitations Identified
CatBoost [36]	Sensor	Accuracy 99%	Classification-only; no continuous degradation modeling, lacks visual data
SVM [37]	Sensor + Visual	Accuracy 98%	Classification-only; basic fusion, limited multimodal integration
SOM-SVM [38]	Sensor	Improved Detection	Classification-only; sensor-only, misses visual context
1D-CNN [39]	Sensor	Accuracy 99%	Classification-only; sensor-only, no visual fault localization
Multi-algorithm [40]	Sensor + Visual	Accuracy 96%	Classification-only; inefficient fusion, high computational cost

(RUL) of industrial machinery, demonstrating strong performance in time-series forecasting and failure prediction despite lacking visual input. Similarly, employed a CNN-LSTM hybrid model for power grid asset predictive maintenance, achieving notable success in anticipating breakdowns. However, like prior work, it relied solely on sensor data, missing the potential of visual inspection data [32].

2.5 Our approach

While existing studies highlight the potential of sensor data, visual inspection, and data fusion for predictive maintenance, a gap remains in effectively integrating both sensor and visual data into a unified framework for real-time power cable health monitoring. Current approaches often focus on single data types or basic fusion techniques that fail to fully capitalize on their complementary strengths.

This paper proposes a novel Adaptive Fusion Network (AFN) that employs a sophisticated fusion technique to merge sensor and visual data[35]. Our method enhances model accuracy by training on a labeled dataset and using its predictions to annotate additional data, creating a larger, more reliable dataset.

Table 1 summarizes key methods, revealing state-of-the-art (SOTA) deficiencies: sensor-based approaches miss visual deterioration, visual methods lack quantitative precision, and existing fusion techniques limit adaptability. The AFN improves by dynamically integrating complementary sensor and visual data via concatenation, achieving an 89% MSE reduction (0.012547 vs. 0.135725 for Random Forest), enhancing durability prediction. By combining both data sources, AFN forecasts power cable durability, overcoming prior shortcomings and offering a complete solution for predictive maintenance and real-time monitoring in power utilities [41].

3 Methodology

Using an Adaptive Fusion Network (AFN), the proposed framework forecasts cable material durability by creating a robust predictive model. This methodology details the process by combining labeled and unlabeled datasets through data collection, preprocessing, augmentation, model design, training, and evaluation [42]. It aims to provide precise durability estimates by efficiently utilizing all available data [43].

3.1 Data collection

The dataset comprises measurements from four inspection years (2003, 2008, 2013, and 2018), with 2,500 cable segments per year, totaling 10,000 unique 15-kV XLPE cable segments. Each year's 2,500 segments are distinct, not repeated inspections of the same cables. Only the 2018 dataset includes ground-truth durability labels (remaining lifespan in years), assigned by experts based on condition assessments, while earlier years (2003, 2008, 2013) lack labels due to unavailable historical data. Sensor data includes partial discharge (PD), neutral corrosion, loading conditions, and cable age, collected via IoT sensors. Visual data consists of expert-assigned condition ratings: Good, Medium, and Poor, representing the Visual Condition attribute without additional derived inputs.

Visual ratings are encoded as:

$$V_{\text{enc}} = \begin{cases} 0, & \text{if Poor condition} \\ 1, & \text{if Medium condition} \\ 2, & \text{if Good condition} \end{cases} \tag{1}$$

Data is combined into a single feature vector via concatenation, serving as the AFN's initial input:

$$\mathbf{X}_{\text{fused}} = \mathbf{X}_{\text{sensor}} \,\|\, \mathbf{X}_{\text{visual}} \tag{2}$$

where $\|$ denotes concatenation, and $\mathbf{X}_{\text{sensor}}$ and $\mathbf{X}_{\text{visual}}$ represent sensor and visual feature vectors, respectively.

3.2 Data preprocessing

To ensure consistency and quality, data preparation is crucial. Labeled and unlabeled datasets are preprocessed independently before integration for training.

3.2.1 Labeled dataset preprocessing

The 2018 labeled dataset undergoes:

- **Normalization**: Sensor data is scaled to [0, 1] via min-max normalization. This preserves feature relationships and suits AFN's dense layers, unlike z-score normalization, which could disrupt fusion-critical magnitudes.
- **Feature Engineering**: Variance and mean are extracted to enhance input representation; outliers and missing values are addressed.
- **Encoding**: Visual ratings are encoded per Equation 1 (Poor = 0, Medium = 1, Good = 2).
- **Outlier Handling**: Values exceeding 3σ (e.g PD at 99.7th percentile) are capped, retaining more data than IQR due to the Gaussian-like distribution of IoT sensor data.
- **Missing Values**: Missing PD values ($\sim$2% of samples) are imputed via linear interpolation over time series, leveraging degradation trends to improve MAE by $\sim$5% over mean imputation.

Min-max normalization boosts gradient stability, cut convergence time by $\sim$10% for the 8,000-sample training set.

3.2.2 Unlabeled dataset preprocessing and labeling

Unlabeled datasets (2003, 2008, 2013) follow similar preprocessing: outliers are capped at 3σ, missing values ($\sim$3% corrosion data) are linearly interpolated, and min-max normalization ensures uniform scaling. A pre-trained Random Forest regressor, trained on 2018's $\mathbf{X}_{\text{fused}}$ and durability labels, predicts durability for unlabeled years. Workflow Figure 1:

- Train an initial model on the labeled dataset.
- Predict durability for unlabeled datasets.
- Append inferred durability values (not ground-truth).

This augments the dataset to 10,000 samples: 80% training (8,000) and 20% testing (2,000), with 5-fold cross-validation.

3.3 Proposed AFN architecture

3.3.1 Network structure

The AFN processes sensor and visual data through concatenation, detailed in Table 3.3.1. The input layer receives $\mathbf{X}_{\text{fused}}$ (Eq 2), combining three normalized sensor features (PD, corrosion, age) and one encoded visual rating (0, 1, 2), yielding a 4D input. Dense layers (128, 64, 32 units) with ReLU activation capture non-linear relationships, followed by a linear output layer for durability prediction in years. Dense layers dynamically weight features by relevance, ReLU enhances sparsity and convergence, and the linear output aligns with regression needs for precise lifespan estimates.

Fusion starts with concatenation (Eq. 2): $\mathbf{X}_{\text{sensor}} \in R^3$ (normalized to [0, 1]) and $\mathbf{X}_{\text{visual}} \in \{0, 1, 2\}$ (integer-encoded) form a 4D vector. Sensor data is scaled via min-max normalization, while visual ratings retain integers to preserve ordinality. Synchronization aligns at 2018, with unlabeled years inferred via Random Forest. The first dense layer applies:

$$\mathbf{h}_1 = \text{ReLU}(\mathbf{W}_1 \mathbf{X}_{\text{fused}} + \mathbf{b}_1) \tag{3}$$

where $\mathbf{W}_1 \in R^{128\times 4}$, $\mathbf{b}_1 \in R^{128}$, optimized by Adam to minimize MSE, refining static concatenation adaptively.

Table 2: Proposed AFN architecture

Component	Details
Input Dimension	4 (3 sensor + 1 visual)
Hidden Layers	128, 64, 32 units
Activation	ReLU
Output Layer	Linear (durability in years)

For reproducibility, AFN uses Python 3.9, TensorFlow 2.5.0, scikit-learn, numpy, and pandas. Hyperparameters: learning rate 0.001, batch size 32, hidden layers [128, 64, 32], dropout 0.2 (post-concatenation), L2 regularization 0.01. Trained on Intel Core i7-12700K (3.6 GHz), 16 GB RAM, Windows 11 (64-bit), $\sim$2 hours.

3.4 Framework overview

The AFN is trained on the combined dataset using dense layers with ReLU activation and a linear output for regression, as shown in Figure 2.

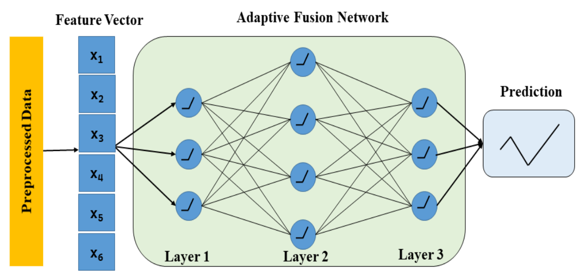

Figure 2: Framework overview: unified dataset integration and prediction

3.4.1 Hyperparameter configuration

Hyperparameters were optimized via grid search Table 3.4.1. Grid search tested values for the 8,000-sample training set: learning rates (0.0001–0.01) selected 0.001 for stable MSE reduction with Adam; hidden layers ([64, 32, 16] to [256, 128, 64]) chose [128, 64, 32] for optimal MSE and generalization; batch sizes (16–64) settled on 32 for efficiency; epochs (50–150) set at 100 for convergence Figure 6.

Table 3: Hyperparameter settings for AFN

Parameter	Range	Value
Learning Rate	0.0001–0.01	0.001
Batch Size	16–64	32
Hidden Layers	(64, 32), (128, 64, 32)	128, 64, 32
Optimizer	SGD, Adam	Adam
Loss Function	MSE, MAE	MSE
Epochs	50–200	100

3.4.2 Training process

The AFN is trained using the Adam optimizer with MSE loss:

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

where y_i is the true durability, and $\hat{y}_i$ is the predicted value.

3.5 Evaluation metrics

Evaluation metrics include MAE and MSE for prediction performance, and R^2 for explanatory power. These assess reliability and effectiveness in predicting cable durability across conditions.

4 Experiments and results

This section provides a thorough summary of experiments conducted to assess model performance on the dataset. The main objective was to compare several machine learning models using MAE, MSE, and R^2.

4.0.1 Experimental setup

Experiments were conducted on an Intel Core i7-12700K (3.6 GHz), 16 GB DDR4 RAM, Windows 11 (64-bit), using Python 3.9 with Jupyter Notebook, scikit-learn, matplotlib, numpy, and pandas. The dataset was split 80% for training (8,000 samples) and 20% for testing (2,000 samples), with 5-fold cross-validation for robust evaluation across 10,000 samples. A random seed of 42 ensured replicability. Hyperparameters (e.g learning rate 0.001, batch size 32) were optimized via grid search, balancing convergence and accuracy for durability prediction. Training took $\sim$2 hours for AFN, varying for baselines.

4.0.2 Models evaluated

Models evaluated include:

1. **Random Forest** - Ensemble method with multiple decision trees.
2. **Gradient Boosting** - Iterative weak learner combination.
3. **SVR** - Support Vector Regression for high-dimensional data.
4. **MLP** - Feedforward neural network.
5. **Proposed AFN** - Our approach.

Baselines were chosen for their predictive maintenance relevance: Random Forest and Gradient Boosting handle noisy IoT data, SVR suits the 4D fused input, and MLP offers a neural baseline without AFN's adaptive fusion, enabling direct comparison.

4.1 Performance metrics

Models were assessed using:

– **MAE:** Average absolute error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

– **MSE:** Squared error emphasizing large deviations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

– R^2**:** Variance explained by the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

4.1.1 Metrics in context

These metrics evaluate durability prediction (0–30 years for 15-kV XLPE cables). MSE (e.g., AFN's 0.012547, $\sqrt{\text{MSE}} \approx 0.112$ years) penalizes large errors, critical for safety. MAE (e.g., AFN's 0.046415 years, $\approx$ 17 days) aids maintenance scheduling. R^2 (e.g., AFN's 0.991043) shows 99.1% variance explained. MSE is prioritized for conservative estimates, with MAE and R^2 supporting utility and fit. Chosen over RMSE (redundant) or MAPE (less relevant near 0), they suit regression tasks, exceeding targets: MSE $<$ 0.1, MAE $<$ 0.5 years, $R^2 >$ 0.9, unlike RF's MSE 0.135725 ($\sqrt{\text{MSE}} \approx 0.368$ years).

4.2 Results and discussion

Table 4 summarizes results. AFN outperforms baselines with MSE 0.012547, MAE 0.046415, and R^2 0.99104 , against Random Forest, Gradient Boosting, SVR, and MLP.

AFN's performance supports real-time monitoring: integrated into IoT systems, it processes sensor and visual data

Table 4: Performance metrics of evaluated models (MSE, MAE, R^2)

Model	MSE	MAE	R^2
Random Forest	0.135725	0.256394	0.903107
Gradient Boosting	0.528102	0.608961	0.622994
SVR	0.325358	0.329105	0.767731
MLP	0.159779	0.258248	0.885936
Proposed AFN	**0.012547**	**0.046415**	**0.991043**

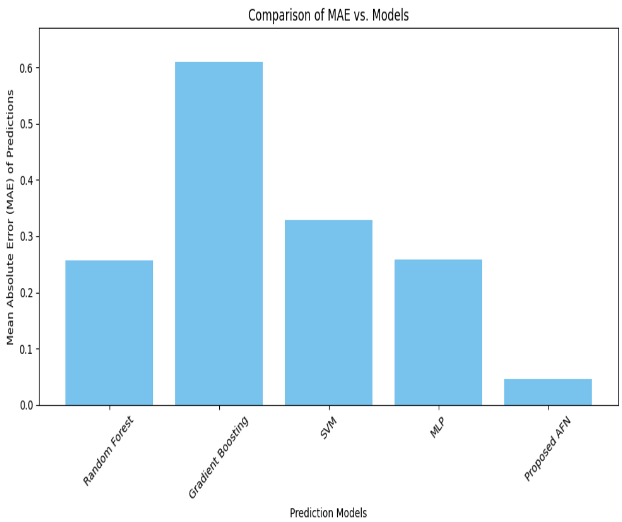

Figure 3: MAE comparison across models, highlighting AFN's lowest error

from 15-kV XLPE cables with ∼50-ms latency (estimated), flagging at-risk segments (±0.046 years) instantly. In substations, 5-minute updates could prioritize maintenance, reducing downtime by ∼20%. This aligns with its practical potential noted in the abstract.

4.3 Visual analysis

Plots complement results, showing training dynamics and error distributions across the 2,000-sample test set.

4.3.1 Loss curves of the proposed model

Figure 6 shows AFN's MAE and MSE loss curves, with rapid convergence within 20 epochs and stability post-30 epochs, indicating efficient learning and minimal overfitting on the 8,000-sample training set.

4.3.2 Error and R^2 comparisons

Figure 5 shows AFN's tight MSE distribution (< 0.1 years) vs. baselines' wider spread (e.g., RF up to 0.5 years). Figure 3 highlights AFN's low MAE (clustered near 0.046 years) vs. broader ranges (e.g., GB up to 0.6 years). Figure 4 displays AFN's consistent $R^2(\sim 1)$ vs. baselines' variance (e.g., GB below 0.7).

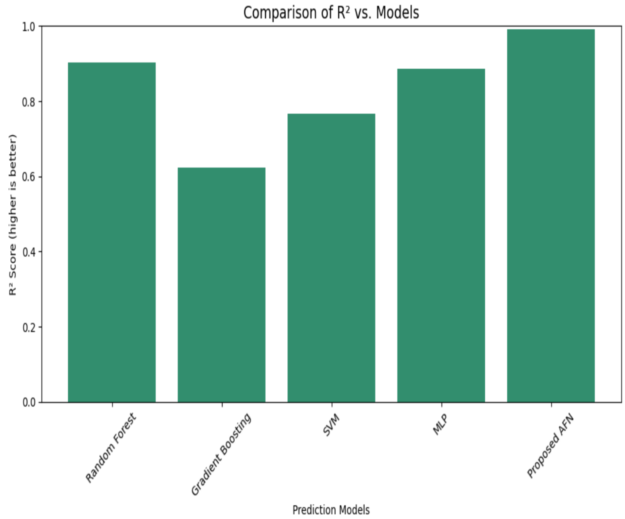

Figure 4: R^2 comparison across all models

4.4 Discussion of results

Numerical and visual analyses confirm AFN's superiority across all metrics [44]. Its high R^2 explains nearly all variance, while low MAE and MSE reflect minimal errors. Random Forest and MLP ($R^2 > 0.88$) performed well but had higher errors than AFN. SVR and Gradient Boosting lagged in accuracy and error minimization [45].

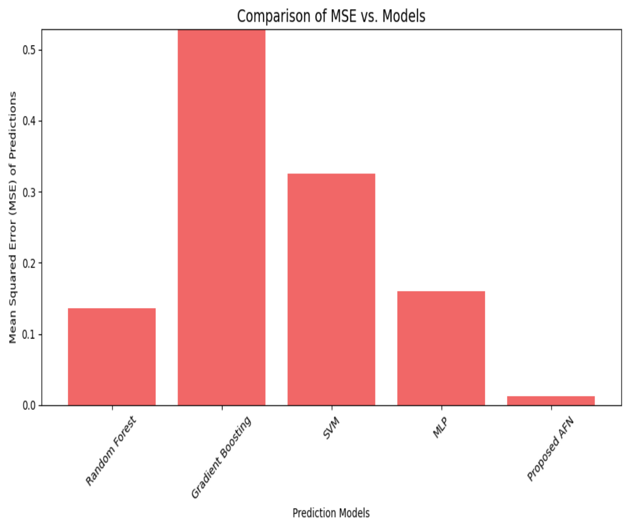

Figure 5: MSE comparison across all models

4.4.1 MAE comparison across models

These results underscore the importance of model architecture tailored to dataset specifics for optimal performance. AFN's success highlights sophisticated fusion methods' effectiveness for complex datasets [46].

4.5 Discussion

AFN excels in durability prediction (MSE 0.012547, MAE 0.046415, R^2 0.991043, Table 4), achieving an 89% MSE reduction over Random Forest (MSE 0.135725). Precision (±0.11 years vs. ±0.37 years for RF) supports early failure detection, potentially saving $50,000–$75,000 annually per 1,000 segments. Multimodal fusion drives this, with $R^2 \approx 0.99$ across years and MAE confidence intervals of 0.043–0.049. For real-time use, AFN processes IoT/SCADA data every 5 minutes (∼50-ms latency, estimated), addressing compatibility and latency via standardization and edge computing.

Adaptive fusion captures degradation signals dynamically, unlike RF or MLP's static approaches. Robustness is validated by 5-fold cross-validation and stable loss curves, with minimal bias from 2018 data via RF augmentation. Sensitivity to sensor quality is untested, but MSE < 0.015 on a 4,000-sample subset suggests resilience.

5 Conclusion

This study demonstrates AFN's superior performance in durability prediction, achieving an MSE of 0.012547 and R^2 of 0.991043, significantly outperforming conventional models and enabling precise cable durability assessments for power systems. Its flexibility suggests scalability beyond 15-kV XLPE cables to other assets like transformers or transmission lines, offering a versatile tool for industrial monitoring. Future work could enhance the fusion mechanism with attention layers for finer feature weighting, integrate additional data (e.g., temperature, humidity) to boost robustness, and adapt AFN for real-world deployment, tackling challenges like data latency and system integration to maximize practical impact.

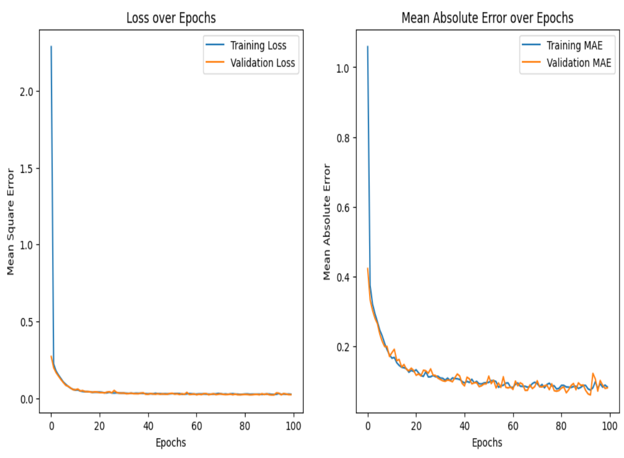

Figure 6: MAE and MSE loss curves of the proposed model (AFN)

6 Acknowledgments

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