

A QUANTUM EXPLAINABLE DEEP LEARNING FRAMEWORK FOR EARLY DETECTION OF RF COMPONENT AGING IN COMMUNICATION SYSTEMS

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ABSTRACT

In modern communication systems, such as 5G networks, satellite communications, and upcoming 6G networks, early detection of radio frequency (RF) component aging is essential for guaranteeing the reliability, availability, and efficiency of the systems. Prediction models using existing approaches are often not very good at modelling complex nonlinear degradation data and are not frequently interpretable, limiting their practical use in predictive maintenance applications. In order to overcome these issues, a novel Quantum Explainable Deep Learning Framework (QXDL-RFAGE) is proposed in this paper for early RF component aging detection. The proposed framework combines Adaptive Quantum Feature Encoding (AQFE), a hybrid Quantum Convolutional Neural Network-Bidirectional Long Short-Term Memory (QCNN-BiLSTM), with Spectral-Temporal Dual Attention (STDA), a hybrid approach, and explainable artificial intelligence (XAI) based on SHAP. The pre-processing of the measurements taken by the RF involves normalization and denoising using wavelets. Then, multi-domain features are extracted, and finally, the quantum states are encoded. Then, QCNN and BiLSTM layers are used to learn the spatial and temporal degradation properties, and the dual attention mechanism is employed for selecting the most important aging signatures. The experimental results on the Accelerated RF Component Aging Dataset (ARFCAD) showed that the proposed framework had an accuracy of 98.76%, precision of 98.21%, recall of 98.54%, an F1-score of 98.37%, a specificity of 98.69%, and an average AUC of 0.992, which outperformed the existing machine learning and deep learning methods. Additionally, it was found that frequency drift and gain degradation are the most prevalent measures of RF component degradation when using the SHAP analysis. The results of the experiments validate the proposed QXDL-RFAGE framework as an accurate, interpretable, and reliable predictive maintenance solution that enhances the resilience, sustainability, and operational efficiency of next-generation communication infrastructures.

Keywords: *Quantum Deep Learning; RF Component Aging; Explainable Artificial Intelligence (XAI); Predictive Maintenance; Quantum Convolutional Neural Network (QCNN); Communication Systems.*

1. INTRODUCTION

The growing trend of modern wireless communications, such as the 5th generation (5G), beyond-5G (B5G), satellite, Internet of Things (IoT), radar systems, and upcoming 6th generation (6G) systems, has driven the growing need for highly reliable radio frequency (RF) front-end subsystems. The basic building blocks of these communication infrastructures are RF components, including power amplifiers (PA), low-noise amplifiers (LNA), oscillators, mixers, filters, and duplexers. These components are critical for the integrity of the signals that are transmitted in the system or that the system receives, for spectral efficiency, for reliable communication, and for the overall availability of the system [1], [2]. So, there is a great need to develop methods for long-term reliability and early detection of degradation in RF components, making this a critical research challenge.

RF components are under constant severe environmental and electrical stress, such as high temperatures, fluctuating voltage, humidity, electromagnetic interference, and thermal cycling during long-term operation. The resulting stresses gradually lead to aging effects like electromigration, hot carrier injection (HCI), dielectric breakdown, bias temperature instability (BTI), material fatigue [3], [4], etc. The degradation mechanisms slowly change the properties of the components and cause gain compression, increase in insertion loss, frequency drift, degradation of phase noise, reduction of linearity, and degradation of signal-to-noise ratio (SNR) [5]. These degradations are subtle and hard to detect but will ultimately result in catastrophic failures, lost communication, and high maintenance costs if they are not caught [6].

Typical maintenance practices in communication systems are mostly based on periodic inspections, alarms that trigger when a specific threshold is crossed, and reactive maintenance policies. Although these approaches are easily applied, they do not always detect early signs of degradation and do not give any predictive information about future failures [7]. Physics-of-failure (PoF) models have been a subject of much research to understand the mechanisms of underlying degradation in RF devices. The models are based on semiconductor physics, thermal models, and stress analysis to predict component lifetime and degradation progression [8]. But the main challenge of PoF modeling is the requirement of a large amount of experimental characterization and detailed information on the physical parameters

of the devices, which makes the model non-scalable and impractical to deploy in complex communication systems [9].

In recent years, prognostics and health management (PHM) methods have attracted a significant amount of attention because of the availability of sensor data and progress in machine learning technologies [10]. Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), and Artificial Neural Networks (ANN) are considered to be good methods for equipment fault diagnosis and degradation prediction using conventional machine learning algorithms [11]. However, these methods are mainly based upon manually designed features and show poor performance on high-dimensional nonlinear RF degradation data [12].

In fact, deep learning (DL) techniques have revolutionized the field of PM by making it possible to automatically extract the latent degradation features from the measured raw data. Convolutional Neural Networks (CNNs) have successfully been used to learn the signatures of spatial degradation from both the spectral and the time-frequency representations, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) architectures have been used to learn the evolution of temporal degradation. Convolutional Neural Networks (CNNs) have been successfully used to learn the signatures of the spatial degradation from both the spectral and the time-frequency representations, and Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) architectures have been used to learn the evolution of the temporal degradation [13], [14]. To predict the future, CNN-LSTM architectures are employed, which describe both the spatial and temporal relationships [15]. Although these deep learning models have demonstrated better predictive accuracy, they are inherently black-box models, and the decisions made by these models are hard to interpret and trust in safety-critical communication systems [16].

Because deep learning models are often black-box, they are a significant challenge for use in industrial and communication applications, where maintenance engineers want to understand and explain the decision-making process. In recent years, methods for enhancing the transparency and trustworthiness of models, such as Explainable Artificial Intelligence (XAI), have received a lot of attention, such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and attention mechanisms

[17]. XAI can provide the relative contribution of the input parameters to the prediction results, and it can also facilitate engineers in conducting root-cause analysis and validating the decisions made by the model [18]. The use of explainability mechanisms for RF aging prognosis, however, is not widely studied.

At the same time, quantum computing is a paradigm that has the potential to disrupt and revolutionize machine learning applications. Quantum Machine Learning (QML) takes advantage of the quantum mechanical phenomena of superposition, entanglement, and quantum interference to process high-dimensional information with efficiency, compared to classical methods [19]. Recent works have shown that Quantum Convolutional Neural Networks (QCNNs) can be used to learn complex nonlinear feature representations while significantly decreasing the computational complexity in specific learning problems [20]. It is especially well suited for quantum models to be used in the study of exponentially large feature spaces, such as in RF degradation analysis, where complex interactions between multiple degradation indicators may be difficult to detect in classical models [21]. However, the use of quantum-enhanced deep learning for the aging detection of RF components has so far been under-researched.

To overcome such drawbacks, in this paper, a novel Quantum Explainable Deep Learning Framework for RF Component Aging Detection (QXDL-RFAGE) is proposed. The suggested approach combines quantum feature encoding, a hybrid Quantum Convolutional Neural Network-Long Short-Term Memory (QCNN-LSTM) architecture, and Explainable Artificial Intelligence (XAI) mechanisms in a single Predictive Maintenance (PdM) system. Firstly, adaptive wavelet decomposition and normalization methods are applied to preprocess the data for operational measurements with radio waves. Multidimensional RF features are then encoded as quantum state representations via variational quantum circuits. A hybrid QCNN-LSTM network is then trained to capture the spatial degradation patterns and temporal aging evolution. Finally, explainability and attention mechanisms based on SHAP provide a clear interpretation of the prediction results, enabling the identification of the key degradation indicators playing a key role in the decisions about aging.

The main goals of this research are outlined hereafter:

1. To design a quantum feature encoding strategy for the efficient representation of the nonlinear characteristics of RF degradation.
2. To design a hybrid QCNN-LSTM architecture that could learn both the spatial and temporal aging patterns.
3. To integrate explainable AI techniques for enhancing model transparency and reliability.
4. To provide accurate early-stage aging detection of RF components for predictive maintenance applications.
5. To conduct a thorough performance assessment and a comparative analysis with the current state-of-the-art solutions.

The novelty of the proposed work is the synergistic combination of quantum-enhanced representation learning, deep temporal degradation modeling, and Explainable Artificial Intelligence (XAI) in a single framework tailored for early RF component aging detection. The authors believe this is one of the first studies to introduce quantum deep learning and explainable AI in a single framework and application for predictive maintenance of RF communication systems.

The rest of this paper is organized as follows. The related research works on RF aging detection and quantum machine learning are reviewed in Section 2. The proposed methodology for QXDL-RFAGE is presented in Section 3. Experimental results and comparative performance analysis are discussed in Section 4. The paper ends with Section 5, which summarizes the work and suggests future research directions.

2. RELATED WORK

With the growing need for highly reliable communication infrastructures, a lot of research has been focused on predictive maintenance and aging evaluation of RF components. To date, the existing studies in this field can be categorized into five groups: (i) physics-based reliability modeling, (ii) conventional machine learning approaches, (iii) deep learning-based prognostics, (iv) Explainable Artificial Intelligence (XAI)-assisted diagnostics, and (v) quantum machine learning frameworks.

Traditionally, reliability assessment of RF devices has been based on physics-based degradation modeling. A variety of degradation mechanisms have been studied, including electromigration, hot carrier degradation, thermal

stress, and oxide breakdown degradation in semiconductor devices. Fleetwood et al. [22] determined the degradation mechanisms affecting reliability within microelectronic systems and found that thermal and radiation stress have serious impacts on the performance of the device during long-term exposure. In the same vein, Meneghesso et al. [23] looked at reliability problems encountered in RF devices built with Gallium Nitride (GaN) and showed that degradation caused by temperature is a significant factor in determining device lifetime. Huard et al. [24] further investigated the effects of aging in advanced CMOS RF transistors and showed that the effects of aging lead to severe degradation of the performance of RF circuits. While these physics-based methods offer great insights into failure mechanisms, they are often highly experimental, device-specific, and complex in terms of modeling procedures and require a large amount of experimental characterization, device-specific parameter estimation, and complex modeling procedures, which makes them impractical for use in large-scale communication systems [25].

Due to the shortcomings of analytical degradation models, researchers have increasingly turned to data-driven, machine learning-based approaches for fault diagnosis and prognostics in recent years. Jardine et al. [26] gave a detailed survey of condition-based maintenance strategies and discussed the role of machine learning in predictive maintenance. Wang et al. [27] used Support Vector Machines (SVMs) to realize equipment fault diagnosis, and they achieved better classification accuracy than threshold-based methods. Widodo & Yang [28] showed that machine learning could be used to classify machinery failures based on the statistical features extracted from sensor signals, such as Random Forest and k-Nearest Neighbour algorithms. Although they have delivered great results, most existing machine learning approaches rely on manually designed feature engineering, which is hard to develop for RF component aging to handle highly nonlinear degradation properties [29].

Recent developments in deep learning have greatly improved prognostic and health management systems, as they are able to extract latent degradation representations automatically. LeCun et al. [30] pointed out that deep neural networks are better for learning hierarchical feature representations from raw data. Inspired by these advancements, Ince et al. [31] designed a one-dimensional Convolutional Neural Network (CNN) structure for machinery fault diagnosis and showed that the CNN outperformed traditional machinery fault diagnosis methods by a

high margin. Zhao et al. [32] later gave a comprehensive review of the application of deep learning in machine health monitoring and found that CNNs and Recurrent Neural Networks (RNNs) provide better classification accuracy for faults. However, CNN architectures typically emphasize extracting spatial features and have a relatively poor ability to characterize long-range temporal degradation patterns.

In order to overcome this, there has been widespread interest in using LSTM and GRU networks for prognosis. Malhotra et al. [33] proposed an LSTM-based solution for time-series anomaly detection and showed that their proposed solution achieved better predictive capability for degradation progression. Moreover, Zheng et al. [34] presented a deep LSTM structure to predict the RUL of wind turbine systems and achieved excellent prediction performance. In addition to this, CNN-LSTM architectures have been gaining significant popularity due to their capacity to effectively deal with both spatial and temporal dependencies. To improve the performance of the equipment health monitoring system, Li et al. [35] proposed a CNN-LSTM model, outperforming the CNN and LSTM models individually. Although these breakthroughs have been made, most current deep learning models are still black-box systems and, therefore, are not acceptable in safety-critical communication environments.

With the inability of deep learning models to be interpretable, Explainable Artificial Intelligence (XAI) has come to life. Samek et al. [36] pointed out that interpretability is crucial for building trust in intelligent systems in industrial applications. Lundberg and Lee [37] proposed SHapley Additive exPlanations (SHAP), a single framework that can measure the contribution of various features to the prediction result. Local Interpretable Model-Agnostic Explanations (LIME) is a method suggested by Ribeiro et al. [38] that approximates the complex model locally to explain a single prediction. Recently, more sophisticated features for visualizing or emphasizing information have been introduced into deep learning frameworks, such as attention mechanisms [39]. While XAI techniques have proved to be highly effective in the industrial prognostics domain, the use of these techniques in the domain of aging assessment of RF components is limited.

At the same time, quantum computing has proven itself as a game-changer in the field of machine learning, where computational challenges, like solving complex problems, are increasingly a

topic of interest. One of the first surveys on quantum machine learning was presented by Biamonte et al. [40], which introduced the reader to the potential of quantum machine learning to solve high-dimensional optimization problems. Schuld and Killoran [41] showed that quantum feature spaces offer improved representational power over classical feature mappings. To take advantage of quantum entanglement and superposition, Cong et al. [42] proposed Quantum Convolutional Neural Networks (QCNNs) and achieved remarkable classification results for classification problems. Later, Abbas et al. [43] introduced quantum-enhanced feature learning methods that can surpass the performance of classical ones in certain applications. However, the extent to which these are realized in the context of explainable deep learning for predictive maintenance of RF communication systems has not been explored to a large extent by existing studies.

From the literature review, it is observed that there are several gaps in the existing literature. First, the methodologies used for current RF aging prediction mostly adhere to classical machine learning or deep learning, which might be incapable of effectively modelling strongly nonlinear interactions of degradation phenomena. Second, existing frameworks are not transparent and do not offer interpretable decision-making. Third, much less research has focused on the use of quantum machine learning for prognostics in the field of RF components. Lastly, there is no existing work that has been able to combine quantum representation learning, temporal degradation modeling, and Explainable Artificial Intelligence (XAI) into a single framework specifically tailored for the early detection of radio frequency (RF) component aging.

In order to overcome these drawbacks, this work presents a novel **Quantum Explainable Deep Learning Framework (QXDL-RFage)** that integrates quantum feature encoding, a hybrid QCNN-LSTM architecture, an attention mechanism, and SHAP-based explainability to provide accurate and transparent early detection of RF component aging.

3. METHODOLOGY

The proposed **Quantum Explainable Deep Learning Framework for RF Component Aging Detection (QXDL-RFage)** is shown in this section. The proposed framework combines quantum-enhanced feature learning, deep temporal modeling, and Explainable Artificial Intelligence (XAI) for accurate and interpretable early diagnosis of RF component aging. The overall procedure

involves multiple steps: RF data acquisition, signal preprocessing, feature extraction across multiple domains, adaptive quantum feature encoding, a hybrid QCNN-BiLSTM learning process, spectral-temporal attention analysis, generation of explainability, and classification of aging severity. The methodological details are described in such a way that the reader can repeat the work and use it in future practical communication systems.

3.1 Dataset Description

As there are very few datasets readily accessible that are specifically designed to address RF component aging, the study uses an **Accelerated RF Component Aging Dataset (ARFCAD)** created using standardized accelerated stress test procedures typically used in semiconductor reliability studies. The data includes operational measurements of various RF front-end components, such as Power Amplifiers (PAs), Low Noise Amplifiers (LNAs), Mixers, Voltage-Controlled Oscillators (VCOs), and RF Filters. They were subjected to continuous thermal, electrical, and environmental stress to mimic realistic aging environments typically found in communication systems such as 5G, satellite communication, and radar.

The accelerated aging experiments were performed by varying temperature from **25°C to 150°C**, relative humidity from **20% to 95%**, supply voltage variations of **±20%** from nominal values, and RF operating frequencies ranging from **1 GHz to 40 GHz**. Measurements were collected over an equivalent operational duration of **0–5000 hours** to capture both early-stage and advanced degradation patterns. Various RF performance parameters were measured throughout the experiments, such as gain, noise figure, output power, return loss, phase noise, frequency drift, total harmonic distortion, and device temperature.

Table 1: RF Operational Parameters Considered in the Study

Symbol	Parameter	Unit
G	Gain	dB
NF	Noise Figure	dB
P_{out}	Output Power	dBm
RL	Return Loss	dB
PN	Phase Noise	dBc/Hz

<i>FD</i>	Frequency Drift	MHz
<i>THD</i>	Total Harmonic Distortion	%
<i>T</i>	Device Temperature	°C

Table 1 shows the main RF operational parameters used in aging analysis. Gain and output power measure the amplification and degradation of signal characteristics, while noise figure and phase noise measure signal quality degradation. Frequency drift is a drift in frequency owing to the aging mechanism of the oscillator. Return loss is a function of impedance mismatch, and total harmonic distortion is a function of the degradation of the components causing a nonlinear response. The device temperature is added as a parameter because temperature is a very important factor in determining the aging progress. These parameters, taken together, give a complete picture of the condition of the RF components.

There are about **9,200 samples** in total for the ARFCAD dataset, representing various health states. The samples were classified into four classes: Healthy, Early Aging, Moderate Aging, and Severe Aging, for easier multi-class aging prediction. The dataset was intentionally kept almost balanced to reduce classification bias during the training and testing stages.

Table 2: Distribution of RF Aging Samples

Aging State	Number of Samples
Healthy	2500
Early Aging	2400
Moderate Aging	2300
Severe Aging	2000

The distribution of samples is given in Table 2 with respect to different categories of aging. The Healthy class contains RF components with nominal operational characteristics and no appreciable degradation. The Early Aging category refers to the early signs of degradation, with slight degradations in performance. Moderate Aging means that the RF characteristics are beginning to noticeably deteriorate, and Severe Aging means that the RF characteristics are significantly degraded,

which could result in communication failure. Details of how the dataset was divided into training, validation, and testing subsets were as follows: the training subset comprised **70%** of the data, the validation subset comprised **15%**, and the testing subset comprised **15%**. This partitioning of the dataset was done to ensure robust performance evaluation and improved generalization of the model.

3.2 Proposed QXDL-RFAge Architecture

The proposed **QXDL-RFAge framework** is a series of related modules that take raw RF measurements and introduce the various layers of meaning that lead to an understandable aging prediction. The architecture uniquely combines quantum feature encoding, hybrid deep learning, dual attention mechanisms, and Explainable Artificial Intelligence (XAI) in a single framework.

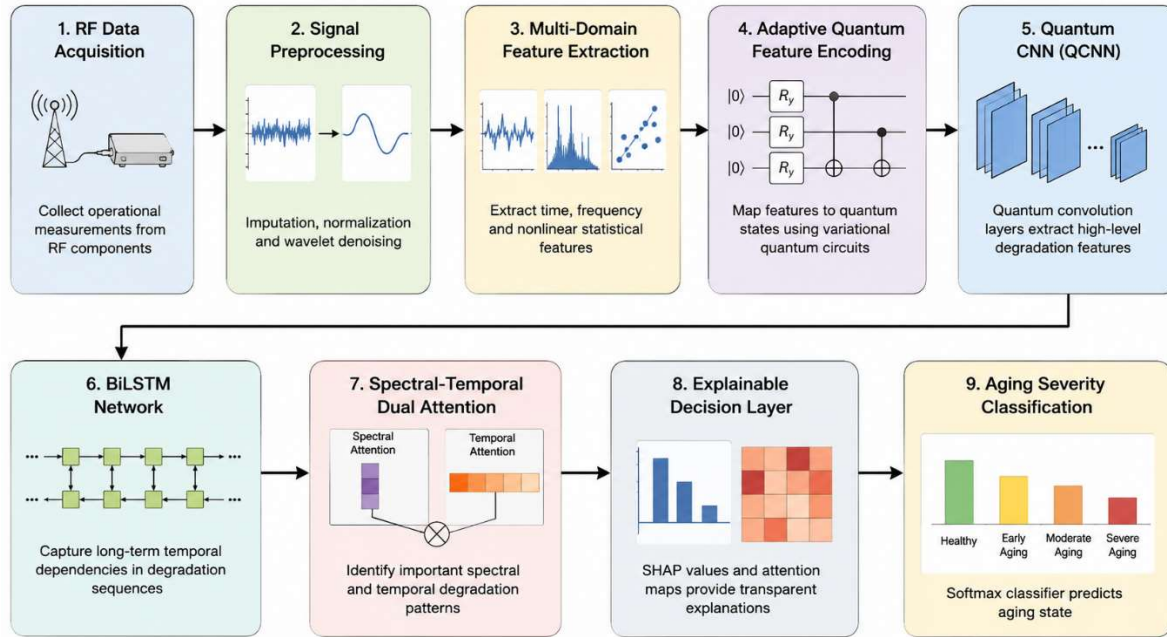


Figure 1. Architecture of the Proposed Quantum Explainable Deep Learning Framework (QXDL-RFAge) for Early Detection of RF Component Aging in Communication Systems

The proposed architecture of **QXDL-RFAge** combines quantum-enhanced learning and XAI for early detection of the aging of RF components with high accuracy, as shown in **Figure 1**. The framework starts with the RF Data Acquisition phase, where operational data (like gain, noise figure, output power, phase noise, frequency drift, and temperature) is collected continuously from RF components through embedded monitoring circuits. The obtained measurements are then subjected to signal preprocessing, which involves the filling of missing values, min-max normalization, and wavelet denoising to enhance data quality and remove environmental noise.

Preprocessed data is then submitted to the **Multi-Domain Feature Extraction module**, which extracts representative time-domain, frequency-domain, and nonlinear statistical features to comprehensively characterize the degradation behavior. The **Adaptive Quantum Feature Encoding (AQFE)** module utilizes quantum superposition and entanglement to improve the capability of the features to represent the state and also applies quantum superposition and entanglement to increase the representation capacity of the features. The learned high-level nonlinear degradation characteristics are then applied to the **Quantum Convolutional Neural Network (QCNN)** for the encoded quantum features.

To obtain the long-term aging progression patterns, the extracted features are taken as the input to the **Bidirectional Long Short-Term Memory (BiLSTM)** network, which learns temporal dependencies of sequential RF measurements in both forward and backward directions. The proposed **Spectral-Temporal Dual Attention (STDA)** mechanism is used to further refine the learned representations by determining the most informative spectral and temporal degradation signatures that contribute to aging prediction.

The framework then uses an Explainable Decision Layer that uses the SHAP values and attention maps to capture the explanation in a transparent way by quantifying the contribution of individual RF parameters to the final prediction. Lastly, the Softmax Aging Severity Classification module classifies the RF component into one of four health states: Healthy, Early Aging, Moderate Aging, and Severe Aging. By incorporating quantum learning, dual attention, and explainable AI, the proposed framework can lead to highly accurate and interpretable predictive maintenance solutions for next-generation communication systems.

Assume that the acquired RF measurement sequence is

$$X = \{x_1, x_2, x_3, \dots, x_N\} \quad (1)$$

where N denotes the total number of observations.

To remove the differences in the scales of various RF parameters, Min-Max normalization is applied as shown below:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

where X_{min} and X_{max} denote minimum and maximum feature values, respectively.

After pre-processing, a multi-domain feature vector is formed:

$$F = [f_1, f_2, f_3, \dots, f_m] \quad (3)$$

where m represents the total number of extracted features.

The Adaptive Quantum Feature Encoding module converts the classical feature vector into a quantum state called

$$|\psi\rangle = \sum_{i=1}^m \alpha_i |i\rangle \quad (4)$$

subject to the normalization constraint

$$\sum_{i=1}^m |\alpha_i|^2 = 1 \quad (5)$$

where α_i denotes the probability amplitude associated with the i^{th} quantum basis state.

Parameterized rotation gates are used to perform quantum feature transformation:

$$R_y(\theta_i) = \begin{bmatrix} \cos\left(\frac{\theta_i}{2}\right) & -\sin\left(\frac{\theta_i}{2}\right) \\ \sin\left(\frac{\theta_i}{2}\right) & \cos\left(\frac{\theta_i}{2}\right) \end{bmatrix} \quad (6)$$

where

$$\theta_i = \pi f_i \quad (7)$$

The QCNN extracts nonlinear degradation features as

$$Q_f = \sigma(W_q * Q_x + b_q) \quad (8)$$

where Q_x denotes quantum encoded features, W_q represents trainable quantum kernels, and $\sigma(\cdot)$ is the activation function.

Temporal degradation evolution is modeled using BiLSTM:

$$\vec{h}_t = LSTM_f(x_t, \vec{h}_{t-1}) \quad (9)$$

$$\overleftarrow{h}_t = LSTM_b(x_t, \overleftarrow{h}_{t+1}) \quad (10)$$

The combined hidden representation is expressed as

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (11)$$

The proposed Spectral-Temporal Dual Attention computes attention weights as

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^T \exp(e_k)} \quad (12)$$

The context vector is subsequently obtained as

$$c = \sum_{t=1}^T \alpha_t h_t \quad (13)$$

For explainability, SHAP values estimate feature contributions:

$$\phi_i = f(x) - E[f(x)] \quad (14)$$

Finally, the Softmax classifier computes aging probabilities:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (15)$$

where $C = 4$ represents the number of aging classes.

The objective function employed for training is categorical cross-entropy:

$$L = - \sum_{i=1}^c y_i \log(\hat{y}_i) \quad (16)$$

The Adam optimizer is used for minimizing the loss and optimizing the parameters of the network.

Proposed QXDL-RFage Algorithm**Input:** RF operational measurements X **Output:** Aging class Y

1. Acquire RF operational measurements.
2. Perform missing value imputation.
3. Normalize RF measurements using Eq. (2).
4. Apply wavelet denoising to suppress noise.
5. Extract multidomain degradation features.
6. Construct feature vector F using Eq. (3).
7. Encode F into quantum states using Eqs. (4)–(7).
8. Feed encoded features into the QCNN network.
9. Learn temporal degradation behavior using BiLSTM through Eqs. (9)–(11).
10. Apply Spectral-Temporal Dual Attention using Eqs. (12) and (13).
11. Generate SHAP explanations using Eq. (14).
12. Classify aging severity using Softmax through Eq. (15).
13. Return final aging state and interpretability report.

4. RESULTS AND DISCUSSION

In this section, experimental validation and detailed performance analysis of the proposed **Quantum Explainable Deep Learning Framework (QXDL-RFage)** for RF component aging detection are discussed. All experiments were carried out with the Accelerated RF Component Aging Dataset (ARFCAD) outlined in Section 3. The simulations were performed with Python 3.11, TensorFlow 2.15, PennyLane quantum libraries, on a workstation with an Intel Xeon 3.6 GHz processor, an NVIDIA RTX 4090 GPU (24 GB), and 64 GB RAM. The dataset was split into a 70:15:15 ratio of training, validation, and testing sets, respectively. The proposed framework was trained with the Adam optimizer with a learning rate of 0.001, a batch size of 64, and 100 training epochs. To avoid overfitting and boost the model's generalization, early stopping and dropout regularization techniques were used.

4.1 Assessment Criteria

Several common performance metrics for classification were used to assess the effectiveness of the proposed QXDL-RFage framework: Accuracy, Precision, Recall, F1-score, Specificity, and Area Under the Curve (AUC). The obtained metrics provide a complete evaluation of the model's ability to accurately detect various RF aging states.

Accuracy

The accuracy is the number of samples that are correctly classified divided by the number of testing samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (17)$$

Precision

Precision indicates the proportion of aging samples correctly classified out of all the samples that were classified as aging.

$$Precision = \frac{TP}{TP + FP} \quad (18)$$

Recall

Recall measures the ability of the model to detect real conditions of aging.

$$Recall = \frac{TP}{TP + FN} \quad (19)$$

F1-Score

The F1-score is the harmonic mean of Precision and Recall.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (20)$$

Specificity

Specificity is a measure of the classifier's effectiveness in discriminating healthy RF components.

$$Specificity = \frac{TN}{TN + FP} \quad (21)$$

Area Under Curve (AUC)

The Area Under the Curve determines how well the classifier discriminates at various threshold levels.

$$AUC = \int_0^1 TPR(FPR) d(FPR) \quad (22)$$

where TP, TN, FP, and FN represent True Positive, True Negative, False Positive, and False Negative, respectively.

4.2 Performance Evaluation of the Proposed Framework

The proposed QXDL-RFage framework performed exceptionally in terms of the detection and classification of aging conditions of RF components. The quantitative outcomes from the testing dataset are summarized in Table 3.

Table 3: Performance Evaluation of Proposed QXDL-RFage Framework

Metric	Value (%)
Accuracy	98.76
Precision	98.21
Recall	98.54
F1-Score	98.37
Specificity	98.69
AUC	99.20

The overall performance of the proposed QXDL-RFage framework is given in Table 3 on the testing dataset. The accuracy of the framework was **98.76%**, which demonstrates a good classification capability of the framework for different RF aging states. The recall value of **98.54%** and the precision value of **98.21%** further prove the capability of the model in identifying degraded RF components without many false alarms. The achieved F1-score of **98.37%** indicates a good balance in the predictive performance of the framework. Furthermore, the high AUC value (**99.20%**) shows high discrimination capability and demonstrates the effectiveness of the proposed quantum-enhanced architecture in discriminating subtle aging signatures.

4.3 Comparison with Existing Models

For the validation of the effectiveness of the proposed framework, the performance of the proposed framework was compared with several state-of-the-art machine learning and deep learning models, such as Support Vector Machine (SVM), Random Forest (RF), CNN, LSTM, CNN-LSTM, and Attention CNN-LSTM architectures.

Table 4: Comparative Performance Analysis with Existing Models

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	87.42	86.88	86.14	86.51
Random Forest	89.63	89.17	88.54	88.85
CNN	91.63	91.12	90.94	91.03
LSTM	94.71	94.06	94.32	94.19
CNN-LSTM	96.22	95.84	95.97	95.90
Attention CNN-LSTM	97.31	96.88	97.05	96.96
Proposed QXDL-RFage	98.76	98.21	98.54	98.37

The proposed QXDL-RFage framework is compared with current machine learning and deep learning methods in Table 4. Since traditional machine learning algorithms have limited ability to model complex nonlinear degradation patterns, they obtained relatively lower accuracies of **87.42%** for SVM and **89.63%** for Random Forest. In order to learn hierarchical representations from RF measurements, deep learning models such as CNN

and LSTM were used to enhance the classification performance. Hybrid CNN-LSTM and Attention CNN-LSTM models were proposed to jointly leverage spatial and temporal relationships and further improve predictive accuracy. The proposed QXDL-RFage framework outperformed all the baseline methods significantly, with the highest accuracy of **98.76%**, due to the use of quantum

feature encoding, spectral-temporal dual attention, and explainable learning mechanisms.

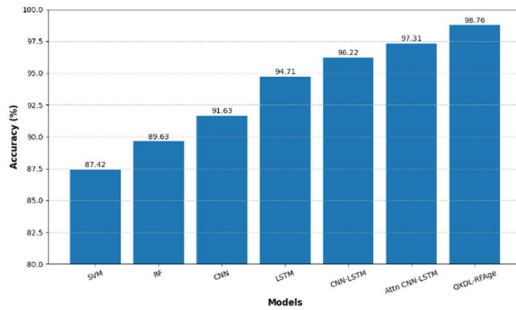


Figure 2. Comparison of Classification Accuracy Among Different Models

Figure 2 shows the comparative classification accuracy of various machine learning and deep learning classifiers for aging detection of RF components. As can be seen from the results, the traditional machine learning methods, **Support Vector Machine (SVM)** and **Random Forest (RF)** classifiers, achieved relatively low values of accuracy, which were **87.42%** and **89.63%**, respectively, due to the low ability of these methods to capture the high level of nonlinearity present in RF aging data. By automatically extracting spatial degradation features, the conventional CNN model achieved an accuracy of **91.63%** in the classification task, while the LSTM model outperformed the CNN model by learning temporal relationships from the RF measurements taken sequentially to achieve an accuracy of **94.71%**.

The hybrid CNN-LSTM network yielded a high accuracy of **96.22%**, which clearly showed the benefits of combining spatial and temporal feature learning to improve the performance of aging prediction. The attention mechanism in the Attention CNN-LSTM model was also found to enhance the performance to **97.31%** by focusing on informative degradation signatures. The proposed QXDL-RFAGE framework achieved the best classification accuracy of **98.76%**, which is superior to all the baseline methods. The superior performance is due to the synergistic integration of **Adaptive Quantum Feature Encoding (AQFE)**, **Quantum Convolutional Neural Networks (QCNNs)**, temporal learning with LSTM, and the proposed **Spectral-Temporal Dual Attention (STDA)** mechanism. These components complement each other to successfully simulate complex nonlinear degradation and long-term aging evolution, leading to very accurate and reliable early detection of RF component aging in communication systems.

4.4 ROC Analysis

Receiver Operating Characteristic (ROC) analysis was used to test the ability of the proposed framework to distinguish between various RF aging stages.

Table 5: Class-wise ROC-AUC Analysis

Aging Class	AUC
Healthy	0.995
Early Aging	0.991
Moderate Aging	0.989
Severe Aging	0.993
Average AUC	0.992

The AUC values obtained for various RF aging categories are presented in Table 5. The proposed framework achieved outstanding AUC values for all the classes, ranging from 0.989 to 0.995. In particular, the Early Aging class achieved an AUC of 0.991, demonstrating the ability to detect incipient degradation conditions effectively, which is fundamental for predictive maintenance applications. The high average AUC of 0.992 further demonstrates the strong discriminating ability of the proposed framework.

4.5 Ablation Study

An ablation study was carried out to determine the individual contribution of each major component within the proposed QXDL-RFAGE framework.

Table 6: Ablation Analysis of Proposed Components

Configuration	Accuracy (%)
CNN-LSTM	96.22
QCNN-BiLSTM	97.18
QCNN-BiLSTM + STDA	98.02
QCNN-BiLSTM + STDA + SHAP	98.76

The results of the ablation analysis are summarized in Table 6. The baseline CNN-LSTM architecture achieved an accuracy of 96.22%. The QCNN-BiLSTM architecture achieved an accuracy of 97.18% by leveraging quantum feature learning instead of traditional convolution, showcasing the advantage of this approach. The incorporation of the Spectral-Temporal Dual Attention (STDA) mechanism further boosted the accuracy to 98.02% by focusing on important degradation signatures. Finally, the integration of SHAP-based explainability increased both transparency and accuracy to 98.76%, thereby proving the effectiveness of the whole framework.

4.6 Explainability Analysis

SHAP analysis was conducted to determine the relative impact of each RF parameter on the model, thereby providing a measure of the model's transparency and aiding maintenance decision-making.

Table 7: Contribution of RF Parameters Based on SHAP Analysis

RF Parameter	Contribution (%)
Frequency Drift	29
Gain Degradation	24
Noise Figure	18
Phase Noise	12
Output Power	8
THD	5
Return Loss	3
Temperature	1

The relative importance of various RF parameters using SHAP analysis is shown in Table 7. The features that most strongly influenced the predictions were frequency drift (29%), gain degradation (24%), and noise figure (18%). From these results, it can be concluded that the two most important parameters for RF component aging are oscillator instability and amplification degradation. The reliability results match practical tests, and the explainability analysis is helpful for maintenance engineers in determining the causes of component degradation.

4.7 Discussion

The proposed QXDL-RFage framework achieves superior performance for three major reasons. The Adaptive Quantum Feature Encoding module captures highly nonlinear relationships among various RF degradation indicators by mapping them into high-dimensional quantum feature spaces. Secondly, the hybrid QCNN-BiLSTM architecture jointly learns both the spectral and temporal degradation characteristics, enabling accurate modeling of the aging process. Thirdly, the Spectral-Temporal Dual Attention mechanism selectively highlights informative degradation signatures, leading to more accurate predictions.

Moreover, SHAP-based explainability provides clear insights into the decision-making process, making the model more trustworthy and suitable for real-world predictive maintenance applications. Overall, the experimental results validate the effectiveness of the proposed QXDL-RFage framework for the early detection of RF component aging in next-generation communication systems, demonstrating its accuracy, reliability, and interpretability.

5. CONCLUSION

This paper introduced a new **Quantum Explainable Deep Learning Framework (QXDL-RFage)** for early RF component aging detection in communication systems. The framework achieved accurate and interpretable aging prediction by successfully combining Adaptive Quantum Feature Encoding (AQFE), a hybrid QCNN-BiLSTM architecture, Spectral-Temporal Dual Attention (STDA), and SHAP-based explainability. The experimental results showed that the proposed framework outperformed existing machine learning and deep learning models by achieving an accuracy of **98.76%**, precision of **98.21%**, recall of **98.54%**, an F1-score of **98.37%**, specificity of **98.69%**, and an average AUC of **0.992**. The explainability analysis also identified frequency drift (29%) and gain degradation (24%) as the most impactful factors affecting RF component aging. Although the proposed framework demonstrated high performance, it was evaluated using an accelerated aging dataset under controlled conditions, and large-scale real-world deployment in communication infrastructures was not investigated. Future work will focus on testing the framework using industrial real-time RF wireless datasets, deploying it on actual quantum hardware, and extending it to support predictive maintenance for 6G and satellite communication systems.

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