Self-Optimizing Autonomous Network Framework for Intelligent Fault Detection and Recovery in 6G Systems

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***Abstract*—In 6G systems, the communication performance is enhanced, and multiple networks and domains interwork in highly complex and dynamic network environments. The traditional Network Management methods have significant challenges in coping with changes in topology size, traffic pattern and faults. In this study, the authors propose a machine learning (ML)-based autonomous (self-)optimizing 6G network framework that facilitates intelligent fault detection and adaptive self-healing capabilities by integrating deep learning (DL), explainable artificial intelligence (XAI), and reinforcement learning (RL). A synthetic dataset with 10,000 data points and different network features is generated and then preprocessed through label encoding, StandardScaler normalization, SMOTE balancing and Recursive Feature Elimination (RFE). Random Forest (RF), XGBoost and Long Short-Term Memory (LSTM) models have been used for fault prediction and analysis, and autonomous recovery and QoS optimization have been achieved using Q-learning-based reinforcement learning. The XGBoost model had the best cross-validation performance, with an accuracy of 0.8637 and ROC-AUC of 0.9476, while LSTM model had the highest testing accuracy (ACC) at 0.8195. A 33.5% reduction in recovery time and an increase in QoS from 48.73 to 55.82 were achieved using the RL-assisted recovery framework. Analysis comparing the suggested LSTM model to CNN, DT, and KNN showed that it performed better. Moreover, LIME and SHAP improved the model interpretability and revealed the important features in the network. The proposed framework constitutes an optimal solution to guarantee reliable, self-healing and adaptive network management for 6G networks.**

Keywords—6G Networks, Intelligent Fault Detection, Reinforcement Learning, Explainable AI, Quality of Service (QoS), Deep Learning

I. INTRODUCTION

Technology is being embraced by society at a rapid pace [1]. As AR, VR, and telepresence become more commonplace, there greater need for next-gen networking capabilities [2]. Although 5G focused on the separation of the digital and physical worlds, the next generation of networking, 6G, is all about the merging of the two [3]. The emphasis on human-machine cooperation creates new use cases that need for networks with unique capabilities and better standards than previous generations [4].

The traditional method of fault detection has been limited to checking for parity checking, hardware redundancy, and expert rules, but these strategies are limited in capability to detect specifically known or unambiguous fault types and/or require knowledge of the expert, and are unsuitable for high-level systems where fault types may be unknown or may change over time [5]. Furthermore, modern electronic systems generate an enormous data stream from sensors, which they cannot manage [6]. With a bit more computational power and access to a wealth of data, a recent leap in ML has made it possible to create intelligent systems for fault detection that can learn from historical and real-time data [7].

Artificial Intelligence (AI) is also crucial in shaping the future of 6G communication systems, facilitating intelligent automation and adaptive network management [8]. ML, DL, and RL are techniques that enable networks to learn from data, predict system performance, and optimize system performance in real-time [9]. These methods can be used in various applications such as resource allocation, mobility management, interference mitigation, energy efficiency, and intelligent fault detection [10]. ML fault detection models outperform their traditional counterparts in a number of important respects, including their capacity to learn and adapt to changing network conditions, pinpoint intricate fault patterns, and boost network and QoS dependability.

A. Motivation and Contributions of the Study

The aim of this work is to overcome the growing complexity, scalability and dynamism of 6G communication networks, where conventional fault management mechanisms are not able to effectively monitor and recover from faults in real time. The framework proposed in this paper enables the QoS and uptime improvements in future 6G networks by providing intelligent fault detection, autonomous recovery and adaptive network optimization, by leveraging ML, DL explainable AI and RL, for reliable and trustworthy self-healing capacity. The major contributions of the proposed research are briefly summarized:

- Synthetic 6G network datasets to simulate network nodes including traffic, latency, packet loss, QoS, energy and recovery-related parameters etc.
- To enhance data reliability and reduce data imbalance, applied data preprocessing methods such as label encoding, feature scaling with StandardScaler, train–test splitting, and class balancing with SMOTE.
- Intelligent fault analysis and self-healing with integrated ML, DL, explainable AI (XAI) and RL techniques for 6G systems.
- Sourced out the proposed framework in terms of the performance metrics like ACC, PRE, REC, F1 and ROC-AUC to ensure reliable performance of the fault detection and prediction process.
- Applied explainable AI techniques to acquire insights on feature relevance and make models more interpretable in the creation of intelligent networks.

B. Justification and Novelty

The proposed work is justified by increasing complexity and dynamic behavior of 6G communication networks, where traditional fault management methods fail to provide efficient real-time monitoring, intelligent fault prediction, and autonomous recovery. The novelty of this study is the combination of intelligent fault detection, explainable AI,

anomaly analysis, AI-driven self-healing through RL, and QoS-aware network optimization into an integrated, autonomous 6G framework. The methodology incorporates the synthetic dataset generation, dataset preprocessing, SMOTE balancing, feature scaling, feature selection, cross-validation, explainability analysis and optimization of adaptive recovery systematically to improve reliability in fault detection, reduce recovery time and boost network performance.

C. *Structure of the Paper*

The paper is structured in the following way: Section II provides a summary of relevant research on 6G network intelligent failure detection and autonomous recovery. Applied explainable AI techniques to acquire insights on feature relevance and make models more interpretable in the creation of intelligent networks. Section III provides specifics of proposed methodology and framework. The experimental results and performance evaluation are covered in Section IV. Section V presents study's main findings and suggests avenues for further investigation.

II. Literature Review

This section reviews ML, DL, explainable AI, and RL techniques used for intelligent fault detection, autonomous recovery, and self-healing optimization in 6G communication networks.

P. P. Kumar et al. (2026) experimental findings indicate the right decision in the best case of 31.6 % and transmit the information in 42% less time and utilize 28% less power as compared to the classic IoV systems. The model recorded the F1 at 0.94 on dynamic traffic of the system as a demonstration of it being successful when coping with shifting mobility environments [11].

S. B. H. Natanzi et al. (2026) the agent's throughput is about the same as a reactive Multi-Armed Bandit (MAB) baseline in a difficult 100-user situation that used the Sionna library. With high data rates maintained and operational dependability comparable to MAB, the suggested architecture enhances connection stability by about 43% over a plain DRL approach [12].

B. Ghale and M. M. Rahman (2025) introduced Intelligent edge-fog computing in IIoT environments using the Novel Adaptive Synergistic Intelligence Framework (NASIF). Comparing NASIF to traditional edge-fog frameworks, experimental investigation on industrial sensor datasets shows that NASIF reduces latency by 37%, improves energy economy by 31%, and increases predictive ACC by 4.8% [13].

S. Mhatre et al. (2025) suggested that the methodology outperforms the state-of-the-art (SOTA) method by 10.67% and DRL-only by 14.28% in terms of throughput for eMBB slices. In comparison to baseline and SOTA methods, it also decreases delay for eMBB slices by 23.57% and 7.48%, respectively [14].

R. Jain (2024) designed an antenna to operate in the THz Band, a crucial 6G band for the impending infrastructure revolution, and optimized its return loss with an MSE of 3.816 utilizing ML models including KNN, XG-Boost, DT, and RF. The results demonstrate that each of the models works as expected, with RF outperforming the others with an 82% success rate in predicting return loss [15]. J. Cai et al. (2024) demonstrated that suggested method increases resource efficiency by up to 33.17% and 41.55%, hence improving network performance. It also increases network throughput by over 70% compared to random algorithms and over 56% compared to Q-Learning techniques [16].

Research Gap: Existing studies mainly focus on network optimization, throughput increase, resource management, and reliability in 6G networks. However, there is insufficient research on intelligent fault detection and recovery, self-explainable AI, and self-healing in the 6G network, which would integrate all aspects into one solution. Also, there is little research on QoS-aware adaptive recovery and autonomous decision-making.

III. Methodology

The proposed methodology includes synthetic 6G dataset generation, preprocessing, SMOTE balancing, feature scaling, and RFE-based feature selection. RF, XGBoost, and LSTM models are used to find faults, and RL is used for self-recovery and improving QoS. Criteria such as ACC, PRE, REC, F1, and ROC-AUC are used to assess model's performance. Shown in Fig. 1 is the overall workflow.

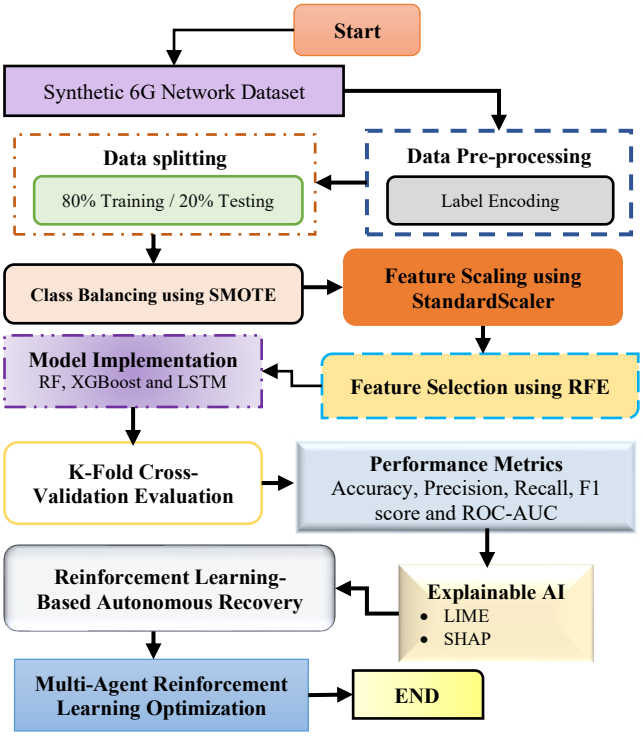

Fig. 1. Flowchart of the Proposed Self-Optimizing Autonomous 6G Fault Detection

A. *Data Collection and Analysis*

The proposed dataset is synthetic, containing 10,000 records and 20 features, generated from 50 simulated network nodes. In order to intelligently detect faults and analyze network performance using DL and ML models, it contains data on network traffic, latency, packet loss, signal strength, CPU utilization, energy consumption, QoS metrics, fault categories, and recovery information.

The interrelationship between different features of 6G network is shown in Fig. 2. The positive or negative correlation between each parameter, such as throughput, latency, QOS score and network efficiency, is shown to detect redundancies and relationships between features.

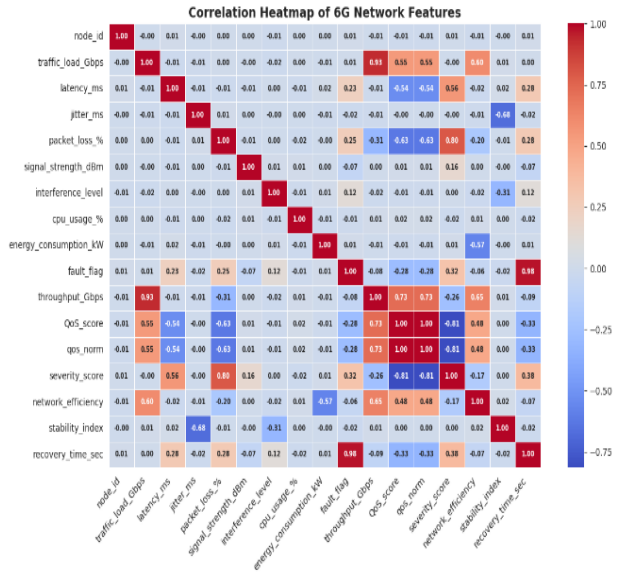

Fig. 2. Correlation Heatmap of 6G Network Features

B. Data Preprocessing

Data pre-processing is done to enhance quality of dataset and make it suitable for ML analysis. Model performance and reliability is improved through the use of preprocessing within the scope of this study. The label encoding is a technique that transforms categorical labels, such as classes related to the fault, into numerical values that ML algorithms can efficiently handle. The purpose of these preprocessing steps is to ensure data consistency, optimize computation, and enable accurate fault detection and network analysis.

C. Data Splitting

The dataset is split in half by code using train_test_split, producing a training set and a testing set. In this case, 80% of data is used to train model, while the remaining 20% is kept for performance evaluation. Make that the split can be reproduced with the random_state=42 option.

D. Class Balancing Using Synthetic Minority Oversampling Technique (SMOTE)

The data is split into training and testing sets before SMOTE is applied to the training set. This fixes the class mismatch problem. This is done on purpose to ensure that no data is leaked and that model's performance on unknown data can be evaluated objectively. Synthetic minority instances are generated by SMOTE through interpolation between existing minority instances, as opposed to merely copying them.

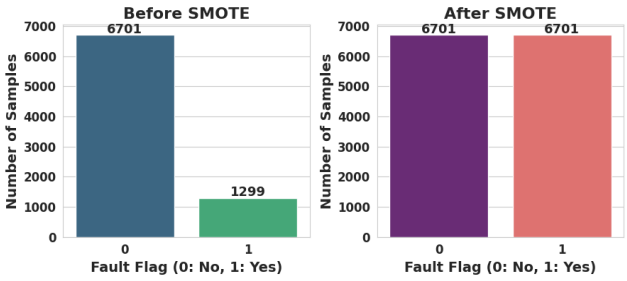

Fig. 3. Class Distribution Before and After SMOTE Balancing

Fig. 3 displays transformation of fault detection dataset's class distribution from pre- to post-SMOTE. The data set is skewed because there are 6,701 non-fault samples and only 1,299 fault samples. When SMOTE is applied to the data set, an equal number of samples in both classes is achieved (each class had 6,701 samples).

E. Feature Scaling using StandardScaler

Data standardization is to change unstructured data into data that follows a predetermined distribution and has predefined characteristics. Its primary goal is to enhance the model's training performance by removing dimensional disparities across features. The standardization processing using StandardScaler module. In order to standardize features, this method examines the raw data, finds their means and standard deviations, and then applies these statistics to each feature. More precisely, it is equal to Equation (1):

$$z = \frac{(x-\mu)}{s} \quad (1)$$

The data standardization value (z), the original data value (x), the original data mean (u), and the standard deviation (s) of the original data are all variables in this context.

F. Feature Selection Using RFE

Feature selection's primary goal is to eliminate inaccurate features while preserving those that can improve the outcomes. In order to make the model more efficient and accurate, only use features that have a high correlation to the target attribute. Implemented RFE as part of the wrapper approach to feature selection. This technique involves partitioning the input data into smaller pieces and then building different models from those pieces. Then, according on predetermined performance parameters, the top features are chosen. Recursive Feature Elimination is used to rank the features according to their relevance, as seen in Fig. 4.

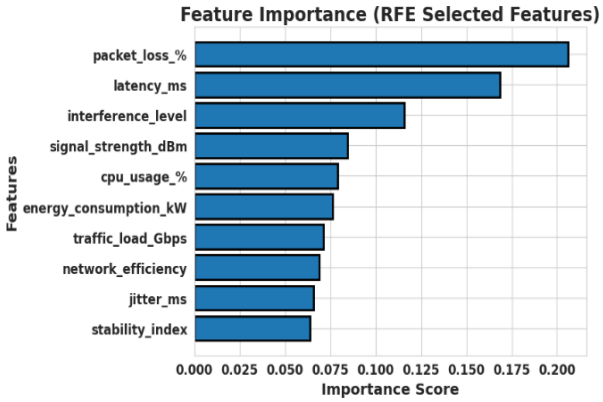

Fig. 4. Feature Importance of RFE Selected Features

The importance of the selected features is presented in Fig. 4 by the Recursive Feature Elimination (RFE) method. From the results, it can be seen that the Packet loss percentage and Latency are the two most important features, followed by interference levels and signal strength respectively.

G. Model Implementation

The proposed framework utilizes RF, XGBoost, and LSTM models for intelligent fault detection and recovery analysis in 6G systems. These models are used to detect network faults, to analyze complex communication patterns and to gain greater ACC and performance of the network.

1) Random Forest

A RF is a group of decision trees constructed separately, each employing a unique subset of the training data and attributes [17]. Bootstrapping or “bagging” adds diversity to the trees in this sampling process. The RF combines the

predictions from the individual trees to return prediction based on majority voting of predictions of trees in the forest for classification task and the average prediction for the regression task. The RF model made use of adjusted hyperparameters to improve model's fault detection performance and classification stability. To improve the prediction ACC, reduce overfitting, and make more reliable fault classifications, the model uses 2000 decision trees, class weighting to balance classes, logarithmic feature selection, and a threshold of 0.65 for class prediction.

2) XGBoost

One robust Gradient Tree Boosting model that can handle massive ML issues is the XGB technique. Being the top performance in every Kaggle competition, it boasts a high predictive ACC and a fast model training speed. Recursively adding trees and dividing features while extending them is the process of XGB. The optimized hyperparameters of the XGBoost model, such as 4000 boosting trees, deep tree structures, regularization, and feature subsampling, improve the reliability of fault classification and predictive performance further, and the threshold of 0.80 is set for the balanced value.

3) Long Short-Term Memory (LSTM)

Sequence data with time-dependent associations, like text and relational data, are best handled by LSTM layer, a subset of RNNs [18]. The LSTM layer houses input gate, shared state, forget gate, and output gate. Below finds use equation and a thorough explanation of how the LSTM layer works:

$$f_s = \sigma\left(W_f \cdot [h_{s-1}, x_s] + b_f\right) \quad (2)$$

$$i_s = \sigma\left(W_f \cdot [h_{s-1}, x_s] + b_i\right) \quad (3)$$

$$\acute{C} = tanh(W_c \cdot [h_{s-1}, x_s] + b_c) \quad (4)$$

$$C_s = f_s \cdot C_{s-1} + i_s \cdot \acute{C} \quad (5)$$

$$O_S = (W_O[h_{s-1}, x_s] + b_C) \quad (6)$$

$$h_s = O_S \cdot \tan(C_s) \quad (7)$$

The forget gate determines the information the LSTM cell forgets (Equation (2)), which is undesirable information in the model. The input gate controls the state update of the LSTM cell according to Equation (3). Equation (4) is used to determine the candidate cell state, and Equation (5) is used to calculate updated cell state. Equation (6) shows operation of output gate, while Equation (7) calculates the last hidden state of the LSTM cell. A two-layer LSTM model with 64 and 32 hidden units, Batch Normalization and Dropout layers, is developed to improve temporal fault learning and alleviate the overfitting issue in 6G networks. In order to train the model to increase the accuracy and consistency of fault detection and prediction, the Adam optimization technique, binary cross-entropy loss, and a balanced threshold of 0.79 are used.

4) K-Fold Cross-Validation for Model Evaluation

The reliability and generalization ability of the proposed fault detection models are tested using the K-Fold Cross-Validation technique in the 6G network. To ensure the stable and consistent performance of the model, a 5-fold Stratified K-Fold approach is applied and the evaluation metrics include ACC, PRE, REC, F1, and ROC-AUC.

H. Performance Metrics

These models are assessed against four benchmark classification metrics: ACC, REC, PRE and F1. ACC is the model's accuracy rate in making predictions; REC is its accuracy rate in classifying attack samples (true positives); PRE is a measure of the reliability of the positive classifications; and F1 is a good metric for imbalanced datasets because it takes the harmonic mean of PRE and REC. Equations (8) to (11) display these measures:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

$$F1-Score = 2 * \frac{(Precision*Recall)}{Precision+Recall} \quad (11)$$

Receiver Operating Characteristic (ROC) Curve: A graph that plots the trade-off between sensitivity and specificity for all thresholds, showing the classification performance across distinct thresholds; the false-positive rate (FPR) is represented on the X axis and the true-positive rate (TPR) on the Y axis.

IV. Result Analysis and Discussion

The purpose of studies is to evaluate efficacy of ML and DL models in 6G networks for intelligent fault detection and autonomous recovery. An enterprise-grade desktop PC running Windows 11 (64-bit), equipped with 32 GB of RAM, an Intel Core i7-10750H CPU clocking in at 2.6 GHz with 16 cores, and a graphics card from NVIDIA called a Quadro T1000, is used for the experiments. Table I displays the results of an investigation of the LSTM model's performance relative to the RF and XGBoost models using the ACC and ROC-AUC metrics. The LSTM model outperformed the others with a maximum testing ACC of 0.8195. Table II shows the cross-validation ACC and ROC-AUC results for the models implemented, with XGBoost achieving the best overall results of CV ACC 0.8637 and CV ROC-AUC 0.9476, highlighting its high reliability and prediction capability in intelligent fault detection and recovery for 6G systems.

TABLE I. Performance Analysis of the Proposed Self-Optimizing Autonomous Network Framework

Model	Accuracy	ROC-AUC
Random Forest	0.8135	0.7265
XGBoost	0.8085	0.7082
LSTM	0.8195	0.7118

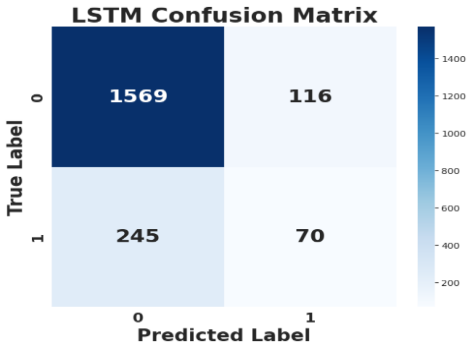

Fig. 5. LSTM Confusion Matrix

The LSTM model's confusion matrix is displayed in Fig. 5. While the model properly identifies 1569 negative samples and 70 positive samples, it wrongly identifies 116 negative samples as positive and 245 positive samples as negative.

Fig. 6 shows ROC curves for RF, XGBoost, and LSTM algorithms for intelligent fault detection in 6G networks.

Among these three algorithms, the one with the highest AUC is the RF algorithm.

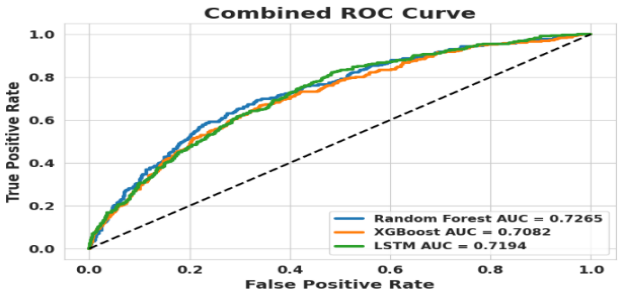

Fig. 6. ROC Curve Analysis of the Proposed Fault Detection Models

TABLE II. CROSS-VALIDATION PERFORMANCE ANALYSIS OF THE PROPOSED MODELS

Metric	Random Forest	XGBoost	LSTM
CV Accuracy	0.8473	0.8637	0.7716
CV Precision	0.8224	0.8076	0.7465
CV Recall	0.8863	0.9549	0.8235
CV F1-Score	0.8531	0.8751	0.7829
CV ROC-AUC	0.9250	0.9476	0.8506

The observed gap between cross-validation and testing performance indicates that the models may experience some degree of overfitting despite the applied regularization techniques. This behavior is attributed to the synthetic nature of the dataset and variations between training and testing samples.

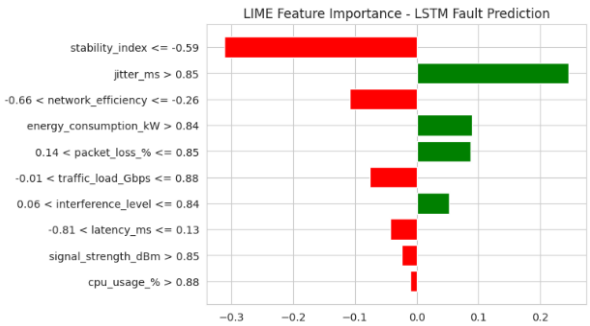

Fig. 7. LIME Feature Importance for LSTM Fault Prediction

The feature importance analysis for the LSTM-based fault prediction model was carried out using LIME, as shown in Fig. 7. The results indicate that high values of jitter (> 0.85) have a positive effect on the fault prediction with an importance value of around 0.26, whereas low values of stability index have a negative effect on the prediction with an importance value of around -0.31.

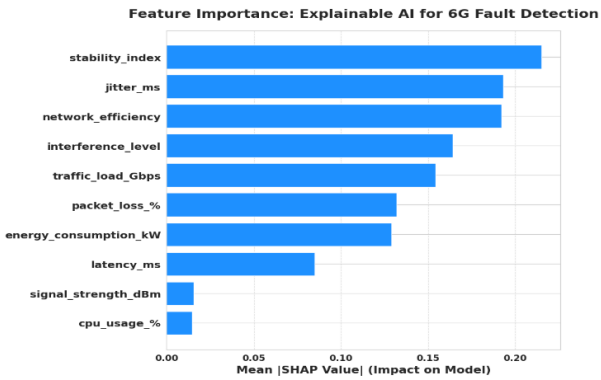

Fig. 8. SHAP Feature Importance for Explainable AI-Based 6G Fault Detection

Fig. 8 displays the results of the SHAP feature importance analysis for the 6G explainable AI fault detection system. The most essential elements, according to the analysis, are the stability index (mean SHAP = 0.22), and jitter (mean SHAP = 0.19). Moreover, the outcomes of the model are strongly influenced by the efficiency of the network, interference and traffic load.

LIME and SHAP provide complementary explanations. LIME explains individual predictions, whereas SHAP measures overall feature importance across the dataset. Therefore, the negative effect of a low stability index in Fig. 7 reflects a specific fault instance, while its high SHAP importance in Fig. 8 indicates that stability index is a critical feature overall. Network operators should use SHAP for global monitoring priorities and LIME for fault-specific analysis.

A. Reinforcement Learning-Based Autonomous Recovery and Network Optimization in 6G Systems

Continuous network parameters such as latency, CPU utilization, signal strength, packet loss, and QoS were discretized into three levels (Low, Medium, and High) using threshold-based binning before applying Q-learning. This reduced the state-space size and prevented Q-table explosion. For large-scale multi-domain 6G networks, future work will investigate scalable Deep Reinforcement Learning approaches such as DQN and PPO.

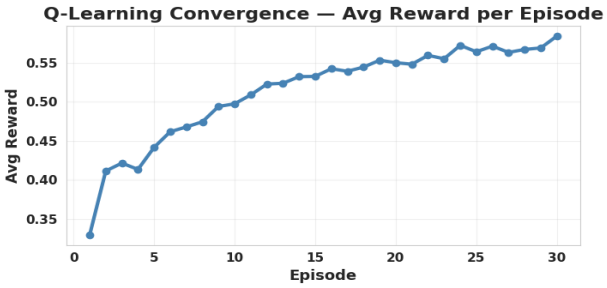

Fig. 9. Q-Learning Convergence – Average Reward per Episode

The proposed 6G framework features RL-based independent recovery system that enhances network performance and fault recovery through the Q-learning algorithm. The method of Q-learning, a value-based RL method, allows the agent to learn optimal decision-making policies by creating associations between state-action pair and the expected future rewards. The model dynamically selects recovery actions, such as rerouting traffic, activating back-up nodes, increasing the bandwidth or restarting nodes to improve the network QoS. After 30 episodes, the RL agent is trained to obtain an average QoS score of 75.5530 with an average reward of 0.6386, while the average score of the EPS-Greedy agent is 74.4791. As shown in Fig. 9, the Q-learning algorithm's average reward comes closer to its optimal value with the progress of training episodes, indicating that the algorithm stabilizes during learning and achieves satisfactory autonomous recovery performance in 6G networks.

B. Closed-Loop ML–RL Framework for Self-Healing 6G Networks

The closed-loop ML–RL framework combines fault detection using the LSTM network with autonomous recovery using RL. The LSTM model identifies network faults, while the RL agent chooses optimal recovery actions by applying the learned Q-table to enhance the network's QoS. The

framework dynamically enables traffic rerouting, bandwidth enhancement, and node recovery, while keeping the system running normally in fault-free situations. Experimental results demonstrate that the framework is able to detect 3168 network faults and enhances the mean QoS from 48.73 before recovery to 55.82 after RL-assisted healing. Moreover, the recovery process based on RL minimizes the recovery time, which shows the efficient adaptive fault management and autonomous decision-making capability of next-generation 6G communication systems.

C. *RL-Based Recovery Time Optimization for Self-Healing 6G Networks*

The recovery time optimization framework based on RL measures effectiveness of autonomous self-healing mechanisms by comparing baseline recovery time in fault conditions with the time saved by RL-assisted recovery. The framework calculates recovery time by considering the network parameters such as latency, packet loss, signal strength, and CPU usage, and the RL agent dynamically determines the best recovery actions to minimize network downtime. The network instances analyzed to measure recovery performance are only those instances impacted by the fault. The experimental results indicate that the baseline recovery time has been decreased from 55.39s to 36.86s with RL-assisted recovery, which represents an average of 33.5% improvement. The recovery time analysis is depicted in Fig. 10, which presents box plots and bar charts, indicating that the RL-based self-healing scheme generally outperforms the baseline system in terms of recovery time for various types of faults, thereby showcasing efficient adaptive recovery and intelligent fault management in 6G networks.

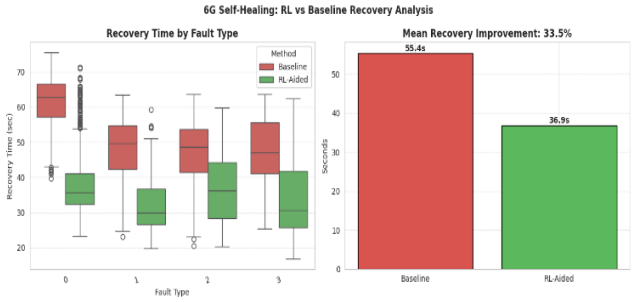

Fig. 10. RL-Based Recovery Time Analysis for Self-Healing 6G Networks

D. *Intelligent Anomaly Detection and Fault Fusion Framework*

The intelligent anomaly detection and fault fusion framework is designed to enhance the autonomous fault analysis in 6G networks by combining anomaly detection and fault detection techniques. The framework detects abnormal network behavior, produces the anomaly flags and integrates them with the identified faults to form a single intelligent fault indicator. A closed loop feedback mechanism checks for QOS improvement following recovery operations. The experimental results reveal that the mean gain in terms of QoS is 1.0739, and 1,498 anomalies were detected and 2,966 intelligent fault instances were identified, which is indicative of effective anomaly detection and adaptive network management.

E. *6G KPI Alignment and Performance Evaluation Framework*

The 6G KPI Alignment framework assesses network performance based on latency, reliability and energy efficiency metrics. These parameters are all used to calculate the final 6G KPI for overall QoS assessment and intelligent network optimization. The mean of the obtained results is 0.5247 for KPI score, which is the result of effective performance evaluation in 6G networks.

F. *Multi-Agent Reinforcement Learning Framework for Autonomous 6G Networks*

MARL is a framework that can be used to achieve autonomous fault recovery for 6G networks, in which each network node is treated as an independent RL agent. Agents employ the Q-learning algorithm to learn optimal recovery actions given the network's current conditions and fault state to optimize QoS and network stability. The reward mechanism encourages good decisions from the recovery process and fault-aware learning. The framework demonstrates effective distributed learning and adaptive self-healing in 6G systems with an average Qos of 74.48 to 76.45 and an average reward of 1.8083 that has been confirmed through experimental results

G. *Real-Time Self-Optimizing Framework for Autonomous 6G Networks*

The real-time self-optimizing framework combines the benefits of LSTM-based fault prediction with the adaptive recovery capabilities of Reinforcement Learning (RL), enabling autonomous management of 6G networks. The framework continually observes the network conditions, foresees potential faults, and dynamically determines recovery operations to optimize the QoS based on Q-learning. In experimental results, it is shown that the framework enhances the average QoS from 74.48 to 76.45, which proves its real-time fault recovery and adaptive self-optimization capability.

H. *Comparison and Discussion*

The ACC performance of various ML models and DL models for intelligent fault detection in 6G networks is shown in Table III. The proposed LSTM model is evaluated with highest ACC of 0.8195. The CNN, DT and KNN models are outperformed by the proposed LSTM model. The outcomes show LSTM model's ability to learn complex network patterns and its better fault detection performance than other methods.

TABLE III. COMPARATIVE ACCURACY ANALYSIS OF THE PROPOSED 6G FAULT DETECTION MODELS

Model	Accuracy
LSTM	0.8195
CNN [19]	0.75
Decision Tree [20]	0.816
KNN [21]	0.6988

The framework proposed here is to utilize the intelligent fault detection in 6G networks using RF, XGBoost and LSTM models. RF yields a higher classification ACC, XGBoost enhances the prediction efficiency and stability of the network, and LSTM can process the patterns of the network time series and predict faults from the network.

V. CONCLUSION AND FUTURE SCOPE

The rapid growth of intelligent communication technologies, autonomous fault management and self-healing mechanisms have become essential for reliable and efficient 6G network operation. The proposed self-optimizing autonomous 6G framework effectively improves intelligent fault detection, autonomous recovery, and QoS optimization

through ML, DL, explainable AI, and RL. Experimental results show that the proposed framework performs well in fault prediction, with a testing ACC of 0.8195 and a ROC-AUC score of 0.9476; it also improves QoS from 48.73 to 55.82 and the recovery time from 55.39 seconds to 36.86 seconds by leveraging the advantages of RL. The incorporation of XAI methods further improves the interpretability of the model by understanding the most relevant parameters of the network that affect fault prediction. The effectiveness is verified by comparative analysis with other current work on intelligent 6G fault management.

This study's use of a synthetic dataset created from simulated 6G network circumstances is one of its limitations. Although the dataset incorporates multiple networks and QoS-related parameters, it may not fully represent the complex traffic dynamics, fault diversity, and operational uncertainties encountered in real-world telecommunication environments. Therefore, Future research will concentrate on leveraging real-world network datasets to validate the suggested methodology and live operational traces to further assess its robustness and practical applicability. Also, focus on stronger regularization strategies, early stopping mechanisms, and validation using real-world 6G network datasets to enhance model robustness and generalization.

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