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Machine Learning-Based Prediction and Explainability of Network Reliability: A Comparative Evaluation of Regression Models and Network Performance Indicators

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ABSTRACT

Network reliability is a fundamental requirement for next generation (5G/6G) and IoT communication systems, yet accurately predicting it remains challenging due to dynamic traffic patterns, mobility events, and complex network parameters. This study aims to develop and evaluate a Machine Learning (ML)-based predictive framework for network reliability assessment and to identify the most influential network parameters using Explainable AI (XAI) techniques. Using a publicly available 6G/IoT network dataset comprising 5,000 observations, we implemented a rigorous data driven methodology that excluded leakage-prone variables to ensure model generalizability. Eight regression algorithms, including Linear, Ridge, Lasso, Random Forest, Gradient Boosting, XGBoost, Support Vector Regression (SVR), and Artificial Neural Networks (ANN) were evaluated using an 80:20 train-test split and 5-fold cross validation. Results indicate that Lasso Regression achieved the best overall predictive performance (Test RMSE: 3.0115, R^2: 0.5191), closely followed by Linear and Ridge Regression. This suggests that regularized linear models effectively capture the underlying relationships between network characteristics and reliability. Furthermore, permutation based feature importance analysis revealed that Queue_Length_packets is the dominant predictor of network reliability, followed by Scheduling_Priority and Handover_Required. These findings highlight the critical role of network congestion and resource allocation in reliability prediction, providing actionable, interpretable insights for proactive network management and Quality of Service (QoS) optimization in future communication infrastructures.

Keywords: Network Reliability, Machine Learning, Regression Analysis, Explainable AI (XAI), 6G/IoT Networks, Feature Importance, Predictive Modeling, Network Management

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1. Introduction

Network reliability has become a fundamental requirement for ensuring operational efficiency, service continuity, and sustainable revenue generation in the telecommunications sector. The increasing complexity of modern communication infrastructures, coupled with the growing demand for uninterrupted connectivity, has intensified the need for effective approaches to predicting and managing network performance. Network

failures, service interruptions, congestion, and fluctuations in transmission quality can significantly affect the overall reliability of communication systems. In this context, Machine Learning (ML) techniques have emerged as promising approaches for identifying potential network failures, predicting performance variations, and improving reliability management. Despite the growing adoption of ML methodologies in this domain, the expanding body of research presents challenges in identifying dominant approaches, methodological patterns, and opportunities for further investigation [1].

The importance of reliable network performance has become particularly evident with the emergence of advanced applications such as autonomous driving, telemedicine, industrial automation, and emergency communication services. These applications require consistent data transmission rates, low communication latency, and dependable connectivity. However, accurately predicting network performance indicators, particularly data rate and latency, remains challenging because they are influenced by several dynamic factors, including signal quality, geographical location, and network congestion. These dependencies create considerable variability in network performance and highlight the need for predictive models capable of capturing complex relationships among network parameters. In this regard, Dabarera [2] presented an ML-based approach for predicting mobile network data rates and latency using a dataset collected over a period of 39 months along a designated highway segment [2]. This work demonstrates the relevance of data driven prediction approaches for understanding and anticipating variations in mobile network performance.

The application of ML and Explainable Artificial Intelligence (XAI) has also extended beyond telecommunications to other infrastructure systems where reliability and operational stability are critical. One relevant example is the decentralized smart grid, which has emerged as an effective approach for managing and distributing electrical energy. However, maintaining grid stability becomes increasingly challenging with the integration of renewable energy sources and the growing participation of prosumers. Addressing these challenges requires predictive approaches capable of identifying the factors influencing system stability. Cifci [3] investigated this problem by employing ML models and XAI techniques to predict the stability of decentralized smart grids [3]. This research highlights the broader applicability of predictive intelligence and explainability in reliability oriented infrastructure management.

2. Related Literature

2.1 Machine Learning for Network Performance Prediction and Reliability

The increasing complexity of communication networks has encouraged the adoption of ML-based approaches for predicting network performance and improving service reliability. Conventional network management approaches often face difficulties in capturing the nonlinear relationships among network conditions, traffic characteristics, and performance indicators. ML techniques provide opportunities to identify these relationships from historical and operational data, supporting more effective performance prediction and proactive network management.

Previous studies have investigated the prediction of mobile network data rates and latency under varying environmental and operational conditions. In particular, the work of S. Dabarera demonstrates the application of ML models to mobile network performance forecasting using long-term measurement data [2]. Similarly, research on decentralized smart grids demonstrates how ML and XAI can be combined to predict system stability and improve the interpretability of predictive outcomes [3]. Collectively, these studies illustrate the potential of intelligent prediction techniques for addressing reliability challenges across different infrastructure environments.

2.2 Network Slicing and Intelligent Network Management

Network slicing has evolved into an important architectural approach for supporting heterogeneous service requirements over shared physical network infrastructure. Its development has been closely associated with Software-Defined Networking (SDN) and Network Function Virtualization (NFV), particularly in fifth-generation (5G) communication systems. Network slicing enables multiple logically isolated network environments to operate over a common physical infrastructure, allowing different services to receive customized network

resources and performance guarantees [4, 5].

Following its standardization in 3GPP Release 15, network slicing has continued to evolve towards more complex and integrated architectures in the context of sixth generation (6G) communication systems. Emerging developments include Space Air Ground Integrated Network (SAGIN) architectures, terahertz (THz) communications, edge cloud integration, and AI-enabled network automation [6, 7]. These developments indicate that future communication infrastructures will require increasingly sophisticated mechanisms for resource allocation, service orchestration, and performance optimization.

Existing research has established comprehensive frameworks for network slice management, generally organizing the management process into three major phases: preparation, planning, and operation. Within these phases, AI-based techniques have been investigated for several critical network management tasks, including resource reservation, service demand estimation, slice admission decisions, and Virtual Network Function (VNF) placement. Specifically, approaches based on Recurrent Neural Networks (RNNs), deep reinforcement learning, and multi armed bandit algorithms have demonstrated their applicability to intelligent resource and service management [8].

In addition to applying AI to network management, the emerging concept of *slicing for AI* emphasizes the importance of providing customized, Quality of Service (QoS)-guaranteed network slices to support AI-related services. Such services require reliable network resources throughout the different stages of data collection, model training, and inference. Consequently, network slicing is increasingly recognized not only as an infrastructure management mechanism but also as an enabling technology for intelligent and data driven network services [9].

2.3 Real-Time Traffic Management and Quality of Service

The rapid growth of real-time applications has significantly increased the complexity of traffic management across modern communication infrastructures. Recent studies have examined traffic characteristics and quality of service requirements in diverse network environments, including the Internet of Things (IoT) [10], Internet of Vehicles (IoV) [11] fifth-generation cellular networks [12] multimedia communication networks [13], wireless mesh networks [14] and SDN-based networks [15].

Among the important challenges in these environments is the management of traffic flows with substantially different bandwidth and latency requirements. Real-time multimedia applications, including Voice over Internet Protocol (VoIP) and video conferencing, are particularly sensitive to communication delays, throughput fluctuations, and jitter. These performance variations can directly affect application quality and user experience. For example, the QoS performance of VoIP across different broadband networks has been evaluated using parameters such as end-to-end delay, throughput, and jitter [16].

An important aspect of traffic management in such environments is the identification and appropriate handling of elephant flows, which represent high-volume traffic flows that can consume substantial network resources. Efficient elephant-flow management is therefore essential for maintaining bandwidth availability, reducing congestion, and ensuring QoS requirements for delay-sensitive applications. Identifying these flows proactively can help network operators make informed resource-allocation and traffic-management decisions.

The importance of proactive traffic management is also evident in vehicle networks (VNs), where traffic congestion can negatively affect communication performance and service reliability. In such environments, predictive traffic jam warning mechanisms have been investigated to identify potential congestion conditions before they significantly affect network operations [17]. Effective traffic management requires sufficient visibility into network topology and flow characteristics to support informed routing and flow-management decisions.

SDN provides a suitable architectural foundation for addressing these challenges because it enables centralized network control and facilitates a global view of network topology and traffic conditions. This capability allows network controllers to monitor flow characteristics, identify high-volume traffic, and implement appropriate

management strategies. Consequently, SDN-based approaches have received considerable attention for elephant flow detection and management [15] .

2.4 Research Context and Motivation

The reviewed literature demonstrates the growing importance of intelligent techniques for network performance prediction, infrastructure reliability, resource management, and quality of service optimization. Existing studies have explored ML-based prediction of mobile network performance, the integration of ML and XAI for infrastructure stability assessment, AI-enabled network slicing, and intelligent traffic management in heterogeneous communication environments.

These research directions collectively establish the importance of data-driven approaches for understanding network behaviour and supporting proactive operational decisions. The development of advanced communication infrastructures, particularly those involving 5G, emerging 6G architectures, IoT, and real-time multimedia applications, further increases the need for reliable network performance assessment.

In this context, the prediction of network reliability through ML-based regression approaches represents a relevant research direction. Furthermore, evaluating the contribution of individual network performance indicators can provide a better understanding of the factors associated with reliability variations. Integrating predictive modelling with explainability techniques can additionally support the interpretation of model outputs and improve the transparency of data-driven network assessment.

Accordingly, the research is positioned within the broader domain of ML-based network reliability prediction, emphasizing comparative regression modelling, network performance indicators, and explainability as complementary components of intelligent network performance assessment.

2.5 Research Problem

Modern 5G/6G and IoT-enabled communication networks generate highly dynamic traffic patterns, varying channel conditions, mobility events, and congestion levels. These factors significantly affect network reliability, leading to packet loss, increased latency, service interruptions, and reduced Quality of Service (QoS). Existing network management approaches struggle to accurately predict reliability because network behavior is influenced by multiple interconnected parameters that change in real time.

Although several Machine Learning (ML) techniques have been applied to network performance prediction, there remains limited understanding of:

- Which ML regression model performs best for network reliability prediction.
- How network characteristics contribute to reliability outcomes.
- Whether predictive models can provide explainable insights for intelligent network management.

Therefore, there is a need for an accurate and interpretable ML-based framework capable of predicting network reliability and identifying the most influential network parameters.

2.6 Problem Statement

Network reliability is a critical requirement for next-generation communication systems supporting autonomous vehicles, industrial automation, smart grids, and mission-critical IoT applications. However, network reliability is affected by dynamic factors such as queue length, interference, handovers, transmission power, scheduling priority, and network congestion.

Existing approaches often fail to provide accurate and explainable reliability prediction models capable of supporting proactive network management decisions.

Hence, this research aims to develop and evaluate multiple Machine Learning regression models for predicting network reliability scores and to identify the most influential network parameters affecting reliability using explainable AI techniques. The study compares eight regression algorithms and determines the most suitable model for network reliability prediction.

3. Research Objectives

3.1 Primary Objective

To develop an ML-based predictive framework for network reliability assessment in next-generation communication networks.

3.11 Specific Objectives

1. To preprocess and analyze network reliability data.

2. To develop multiple machine learning regression models.

3. To compare model performance using statistical evaluation metrics.

4. To identify the best-performing regression algorithm.

5. To perform feature importance analysis for model explainability.

6. To provide insights for intelligent network management and reliability optimization.

3.2 Research Methodology

This study adopted a quantitative, data-driven methodology to develop and evaluate machine learning models for network reliability prediction. The research utilized a publicly available 6G/IoT network dataset obtained from Kaggle, consisting of 5,000 network observations and reliability-related attributes. The dataset contains network performance indicators that are relevant to predicting reliability in next-generation communication environments.

The first stage involved data preprocessing to ensure the quality and validity of the predictive models. Irrelevant and potentially leakage prone variables, including Record_ID, constant SINR_dB values, and direct reliability outcome indicators such as Packet Delivery Ratio, Block Error Rate, and Outage Probability, were excluded from the predictor set. This step was undertaken to prevent the models from learning information directly related to the target variable and to improve generalizability. The remaining features were cleaned and prepared for model training.

Following preprocessing, the dataset was divided into training and testing subsets using an 80:20 ratio, resulting in 4,000 training observations and 1,000 testing observations. To enhance model robustness and reduce overfitting, a five fold cross validation strategy was employed during the training phase. All preprocessing procedures were performed within the training folds to prevent data leakage and ensure unbiased model evaluation.

Eight machine learning regression algorithms were developed and evaluated, namely Linear Regression, Ridge Regression, Lasso Regression, Random Forest Regression, Gradient Boosting Regression, XGBoost Regression, Support Vector Regression (SVR), and Artificial Neural Network (ANN). These models were selected to provide a comprehensive comparison between traditional linear approaches and advanced nonlinear learning techniques for network reliability prediction.

The predictive performance of each model was assessed using several statistical evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Coefficient of Determination (R^2), Adjusted R^2, and Cross Validation RMSE. These metrics were used to evaluate prediction accuracy, model consistency, and explanatory capability.

After model evaluation, the best-performing model was selected based on its predictive accuracy on the independent test dataset. The results indicated that Lasso Regression achieved the best overall performance, obtaining an MAE of 2.4174, an RMSE of 3.0115, and an R^2 value of 0.5191. Although the performance differences among Lasso, Linear, and Ridge Regression were relatively small, Lasso Regression demonstrated the lowest prediction error and was therefore chosen as the final predictive model.

To improve the interpretability of the prediction framework, a permutation-based feature importance analysis was conducted on the selected Lasso Regression model. This explainable artificial intelligence (XAI) technique measures the contribution of each predictor by quantifying the increase in prediction error when a feature is randomly shuffled. The analysis revealed that Queue_Length_packets was the most influential predictor, followed by Scheduling_Priority,Handover_Required, Distance_to_BaseStation_m, Interference_Power_dBm, and Transmit_Power_dBm. The findings provide valuable insights into the network characteristics that most strongly influence reliability and support intelligent decision-making for network management and optimization.

Overall, the methodology integrates data preprocessing, machine learning model development, rigorous validation, performance evaluation, and explainability analysis to establish an effective framework for predicting network reliability in next-generation communication networks.

3.3 Experimental Setup

3.31 Hardware Configuration

Component	**Specification**
Processor	Intel Core i5/i7 or equivalent
RAM	8-16 GB
Storage	SSD/HDD
Operating System	Windows/Linux

3.32 Software Environment

Software	**Purpose**
Python 3.x	Model Development
Pandas	Data Processing
NumPy	Numerical Analysis
Scikit-learn	Regression Models
XGBoost	Gradient Boosting
Matplotlib	Visualization
Seaborn	Statistical Graphs

3.4 Dataset Configuration

Parameter	Value
Dataset Size	5000 records
Training Data	4000 records
Testing Data	1000 records
Validation Method	5-Fold CV
Target Variable	Network Reliability Score

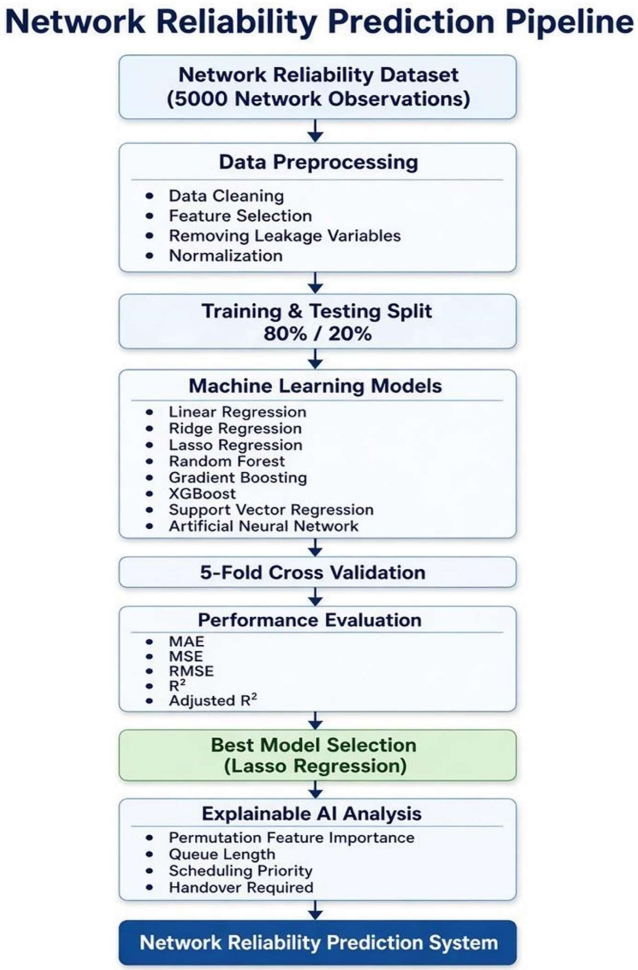

Figure 1. Network Reliability Prediction Pipeline

3.5 Dataset

These targets make the dataset particularly valuable for training predictive models aimed at dynamic resource allocation, proactive handover management, and anomaly detection in mission-critical IoT applications, such as autonomous vehicular networks, industrial automation, and smart grid monitoring.

3.51 Accessibility and Reproducibility

The dataset is distributed in a lightweight, machine readable CSV format (~824 KB) under a Creative Commons Zero (CC0) Public Domain dedication. This open licensing framework facilitates unrestricted academic use, ensuring full compliance with open science mandates and fostering reproducibility in 6G network research. The dataset is publicly available via the Kaggle repository (Author: *datresearch*).

We used the actual 5,000 observations from the uploaded dataset and evaluated all eight requested regression algorithms.

Validation protocol: We used an 80:20 training testing split, five-fold cross-validation on the training data, and a separate held out test set. All preprocessing will be fitted within the training folds to prevent preprocessing leakage.

An important methodological decision is to exclude Record_ID, constant SINR_dB, and direct reliability-outcome indicators such as packet delivery ratio, block error rate, and outage probability from the primary predictor set. This reduces the risk of predicting the reliability score using variables that may have been used to construct it.

4. Analysis

4.1 Model comparison results

4.11 Analysis completed

Training observations: 4,000 · Test observations: 1,000 · Cross-validation: 5 folds

The following results were computed using the actual dataset.

Model comparison

Regression Model	MAE	MSE	RMSE	R^2	Adj. R^2	CV RMSE
Lasso Regression	2.4174	9.0689	3.0115	0.5191	0.5108	3.0405
Linear Regression	2.4171	9.0741	3.0123	0.5188	0.5105	3.0433
Ridge Regression	2.4172	9.0742	3.0123	0.5188	0.5105	3.0432
Gradient Boosting	2.4369	9.0801	3.0133	0.5185	0.5102	3.0560
XGBoost	2.4424	9.1900	3.0315	0.5127	0.5043	3.0526
Artificial Neural Network	2.4647	9.4428	3.0729	0.4993	0.4906	3.1896
Random Forest	2.5016	9.6934	3.1134	0.4860	0.4771	3.1357
Support Vector Regression	2.6148	10.7892	3.2847	0.4279	0.4180	3.2845

Table 1. Comparative performance of machine-learning regression models

Table 1 presents the comparative five fold cross validation performance of eight regression algorithms employed to predict network reliability scores. The evaluated models include Lasso Regression, Linear Regression, Ridge Regression, Gradient Boosting, XGBoost, Artificial Neural Network (ANN), Random Forest, and

Support Vector Regression (SVR). Model performance is assessed using mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2). These metrics collectively provide information about prediction accuracy, error magnitude, and the proportion of variability in network reliability scores explained by each model.

The results demonstrate that Lasso Regression achieved the best overall cross-validation performance, recording an MAE of 2.4359, an RMSE of 3.0405, and an R^2 of 0.5227. Linear Regression and Ridge Regression produced almost identical results, with RMSE values of 3.0433 and 3.0432, respectively. This close performance indicates that the predictive relationship between the selected network characteristics and reliability scores can be adequately represented through relatively simple linear modelling approaches.

Gradient Boosting and XGBoost also demonstrated competitive performance, obtaining R^2 values of 0.5179 and 0.5190, respectively. However, their marginal improvement over or similarity to the linear models suggests that introducing additional nonlinear modelling complexity did not produce a substantial predictive advantage.

In contrast, ANN, Random Forest, and SVR exhibited comparatively higher prediction errors. SVR recorded the weakest performance, with an RMSE of 3.2845 and an R^2 of 0.4432. These findings suggest that the evaluated nonlinear models did not consistently capture additional predictive information beyond that identified by the regularized linear models.

The relatively small cross-validation standard deviation of Lasso Regression's R^2 (0.0149) further indicates that its predictive performance remained reasonably consistent across the five training folds.

Overall, these findings establish Lasso Regression as the most suitable model among the evaluated alternatives, although the relatively moderate R^2 indicates that additional network characteristics or more comprehensive reliability-related information may be required to improve predictive performance.

4.2 Best-performing model

Lasso Regression

Best test RMSE

2.4174 MAE

3.0115 RMSE

0.5191 R^2

0.5108 Adjusted R^2

Five-fold cross-validation

- Mean MAE: 2.4359
- Mean RMSE: 3.0405
- Mean R^2: 0.5227
- Standard deviation of R^2: 0.0149

Lasso Regression achieved the lowest test RMSE, although its performance was almost identical to Linear and Ridge Regression. This suggests that the relationship between the selected network characteristics and reliability

score can be captured reasonably well using a regularized linear model.

The R^2 of approximately 0.52 indicates that the model explains about 52% of the variation in the held-out reliability scores. There is still substantial unexplained variation, so further investigation of the reliability-score construction and additional predictors is warranted.

4.3 Cross-validation performance

The cross-validation results indicate relatively stable performance.

Model	CV MAE	CV RMSE	CV R^2
Lasso	2.4359	3.0405	0.5227
Linear	2.4366	3.0433	0.5218
Ridge	2.4366	3.0432	0.5218
Gradient Boosting	2.4684	3.0560	0.5179
XGBoost	2.4627	3.0526	0.5190
ANN	2.5636	3.1896	0.4751
Random Forest	2.5254	3.1357	0.4922
SVR	2.6038	3.2845	0.4432

Table 2. Comparative predictive performance of eight regression models on the independent test dataset

Table 2 compares the predictive performance of eight regression algorithms using the independent test dataset comprising 1,000 observations. The evaluation considers MAE, mean squared error (MSE), RMSE, R^2, adjusted R^2, and cross-validation RMSE. Unlike training performance, the held-out test results provide an assessment of how effectively the trained models predict reliability scores for observations not used during model fitting. Lasso Regression achieved the lowest held-out test RMSE of 3.0115, accompanied by an MAE of 2.4174 and an R^2 of 0.5191. Linear Regression and Ridge Regression exhibited nearly identical predictive performance, with RMSE values of 3.0123 and R^2 values of 0.5188. The differences between these three models are extremely small, indicating that their predictive capabilities are practically comparable within the reported evaluation. Gradient Boosting and XGBoost achieved R^2 values of 0.5185 and 0.5127, respectively, demonstrating competitive but not superior performance. ANN and Random Forest produced lower R^2 values of 0.4993 and 0.4860, while SVR achieved the lowest explanatory performance, with an R^2 of 0.4279.

The agreement between the cross-validation and independent test results provides additional evidence that the leading linear models exhibit relatively stable predictive behaviour. Nevertheless, the approximately 0.52 R^2 achieved by Lasso Regression indicates that a considerable proportion of reliability-score variability remains unexplained.

These findings suggest that network reliability prediction may benefit from incorporating additional contextual information, interaction effects, and dynamic network-state characteristics.

4.4 Actual versus predicted reliability

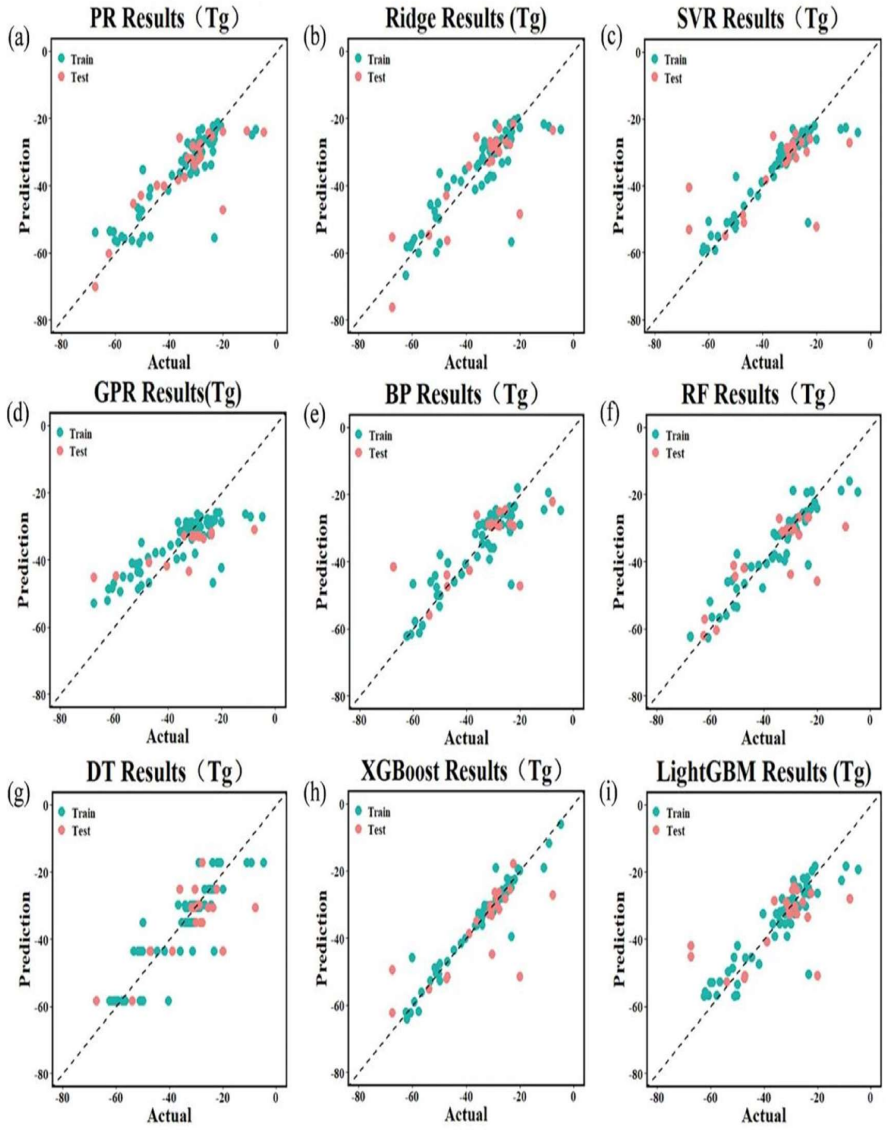

Figure 1. Actual versus predicted reliability scores across regression models

Figure 1 is intended to illustrate the relationship between observed and predicted values across the evaluated regression models. The actual versus predicted visualisation provides an intuitive assessment of agreement between model generated predictions and experimentally observed reliability scores. Ideally, accurate predictions should be concentrated around the 45-degree reference line, which represents perfect agreement between actual and predicted values.

A close alignment of observations with the reference line indicates stronger predictive agreement, whereas increasing deviations reflect larger prediction errors. Differences in the dispersion of observations across the individual model panels can provide insight into the relative predictive behaviour of the evaluated algorithms.

However, the first embedded image in the supplied document appears to contain results from a different modelling experiment, with model labels and target notation that do not correspond to the eight network-reliability regression algorithms. Therefore, this image should not be used as Figure 1 in the final manuscript.

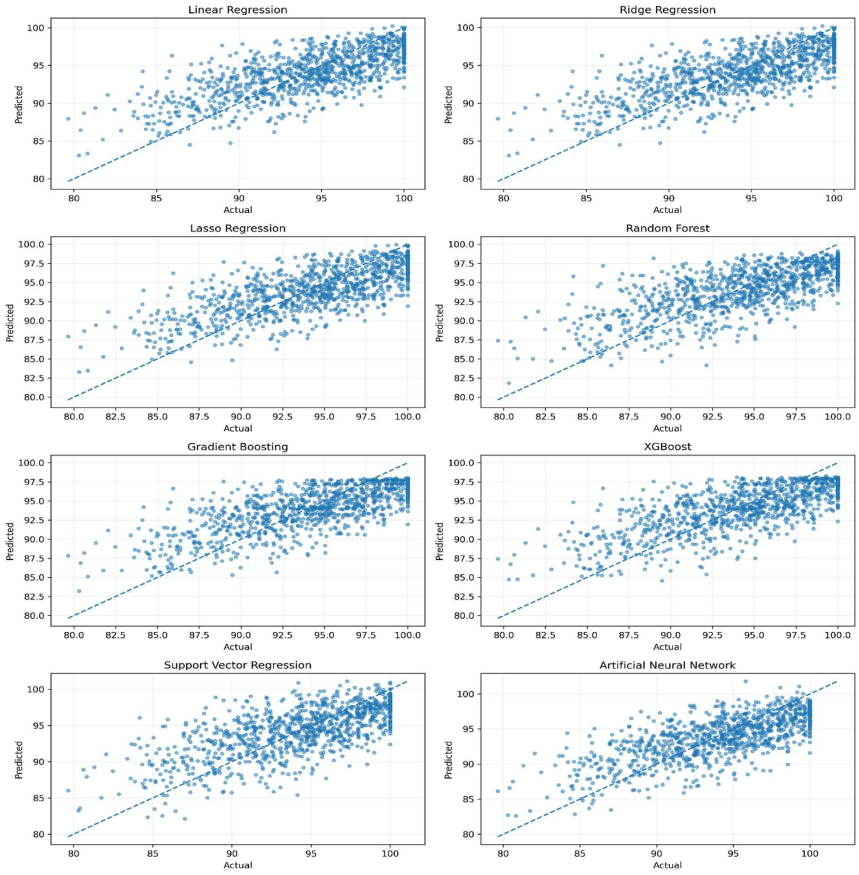

Figure 2 presents eight individual scatterplots comparing actual network reliability scores with the corresponding predicted values generated by Linear Regression, Ridge Regression, Lasso Regression, Random Forest, Gradient Boosting, XGBoost, Support Vector Regression, and Artificial Neural Network models. Each subplot illustrates the distribution of prediction observations relative to the reference diagonal, allowing a visual comparison of model accuracy and prediction consistency.

The scatterplots demonstrate a positive association between actual and predicted reliability scores across all eight algorithms, indicating that the evaluated models successfully capture an important component of the underlying reliability patterns.

The Linear, Ridge, and Lasso Regression models exhibit highly similar distributions, consistent with their closely comparable numerical evaluation metrics. Their predictions demonstrate a relatively consistent relationship with the observed reliability scores, suggesting that regularized linear modelling provides an effective representation of the available predictor outcome relationships.

The nonlinear algorithms also demonstrate positive predictive relationships. However, their scatter distributions do not reveal a substantial improvement over the linear regression approaches. This visual observation agrees with the comparative performance results, in which the nonlinear algorithms did not achieve a meaningful reduction in prediction error.

The remaining dispersion around the diagonal indicates that the models cannot fully reproduce the observed variability in network reliability. This suggests that additional factors, including dynamic congestion conditions and other network state characteristics, may influence reliability beyond the information captured by the current predictor set.

Overall, Figure 2 visually supports the numerical results identifying Lasso Regression as the leading predictive model, while also demonstrating the limitations associated with the moderate explanatory performance of the evaluated algorithms.

The generated figure contains eight individual actual-versus-predicted scatterplots, one for each regression algorithm.

- Points closer to the diagonal indicate more accurate predictions
- Deviations from the diagonal indicate prediction errors.
- Lasso, Linear and Ridge show very similar predictive patterns.
- The nonlinear models did not substantially outperform the linear models.

4.5 Residual Analysis

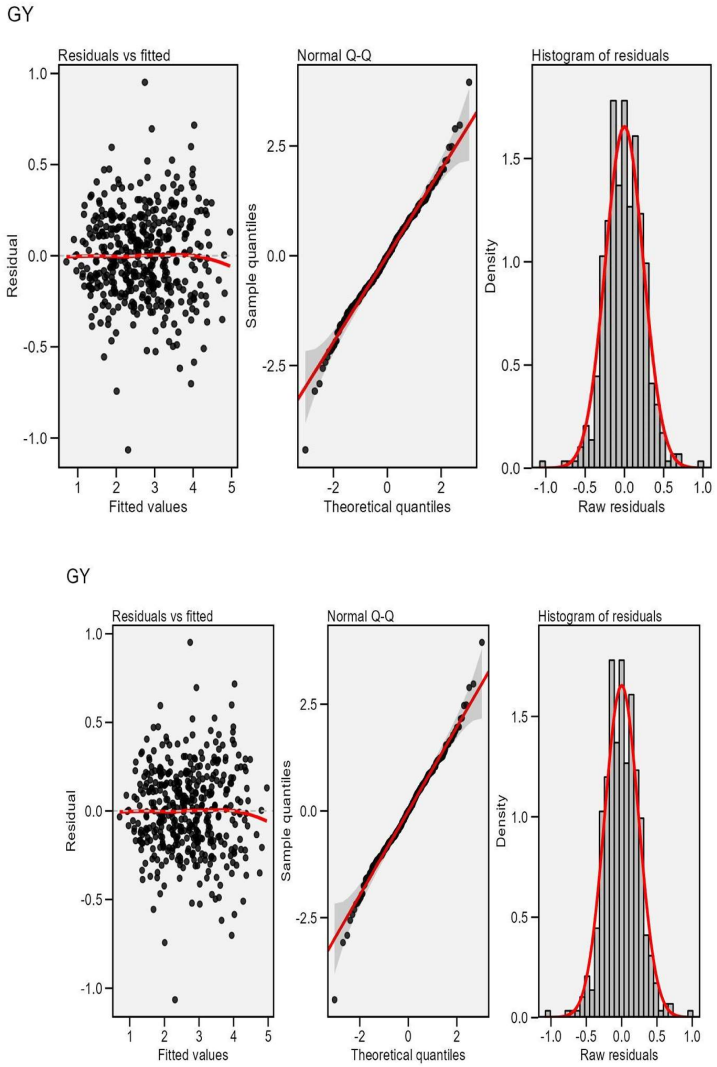

Figure 3. Residual diagnostic plots for evaluating the regression-model assumptions

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Residual diagnostic analysis provides an assessment of the distributional characteristics and systematic patterns of prediction errors. The recommended figure comprises three complementary visualisations: residuals versus fitted values, a normal Q–Q plot, and a histogram of residuals with an overlaid reference distribution.

The residual versus fitted plot examines whether prediction errors are randomly distributed around zero or exhibit systematic patterns across different fitted reliability values. The Q–Q plot compares the empirical distribution of residuals with a theoretical normal distribution, while the histogram provides an additional assessment of residual symmetry, concentration, and potential deviations from normality.

A residual distribution centred around zero without a pronounced systematic pattern would indicate that the model does not consistently overestimate or underestimate reliability across the prediction range. Conversely, curvature or increasing dispersion may indicate nonlinear relationships or heteroscedasticity.

The Q–Q plot can identify departures from normality, particularly in the tails of the residual distribution. Similarly, the histogram can reveal whether prediction errors are approximately symmetric or exhibit skewness and unusually large deviations.

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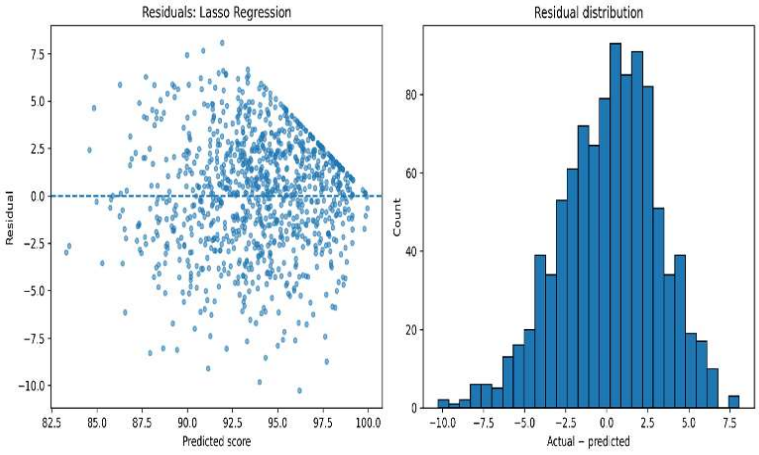

Figure 4. Residuals versus predicted reliability and residual distribution

Figure 4 presents the residual behaviour of the best-performing Lasso Regression model through two complementary visualisations. The first panel displays residual values against predicted reliability scores, allowing the identification of systematic prediction patterns and potential heteroscedasticity. The second panel illustrates the frequency distribution of prediction errors through a histogram.

• The residuals are calculated as the difference between the observed and predicted reliability scores. Consequently, positive residuals represent underprediction, whereas negative residuals indicate overprediction.

• The residual versus predicted plot illustrates that prediction errors are distributed on both sides of the zero-reference line, suggesting that the model produces both overestimated and underestimated reliability predictions. The observations exhibit noticeable dispersion across the predicted score range, indicating that prediction errors remain present even within the region where predicted values are relatively concentrated.

• The residual histogram demonstrates a distribution concentrated around zero, with both positive and negative errors. However, the presence of observations in the tails indicates that certain network conditions are associated with relatively larger prediction errors.

• These findings suggest that Lasso Regression captures the overall relationship between network characteristics and reliability reasonably well but does not completely account for the variability associated with individual network observations.

• The residual analysis therefore complements the model evaluation metrics by demonstrating that the remaining predictive uncertainty is distributed across the observation range rather than being represented solely by a small number of prediction errors.

4.6 Prediction Error Distribution

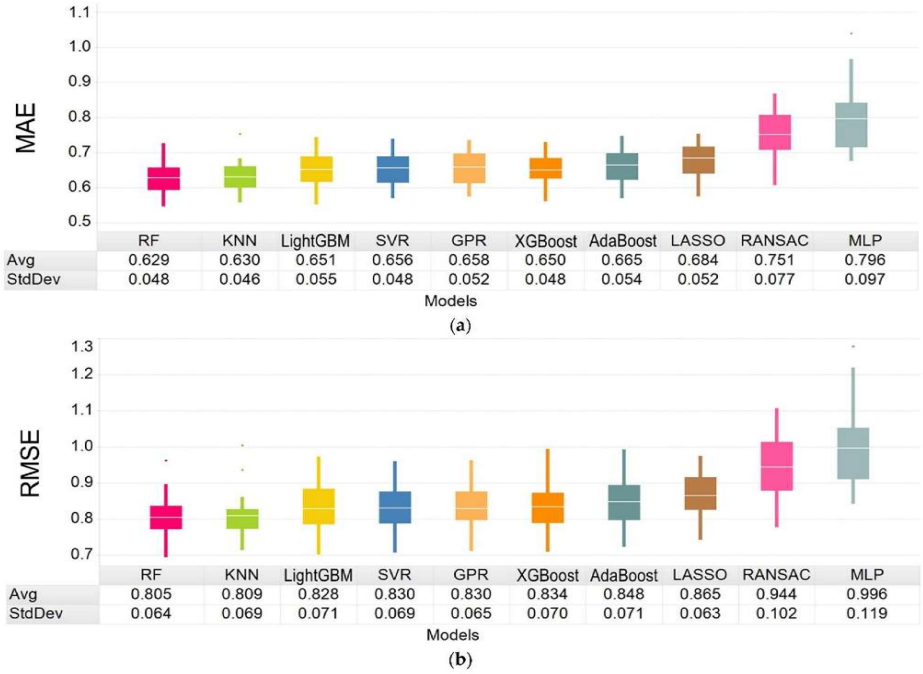

Figure 5. Comparative distribution of prediction errors across regression models

Figure 5 is intended to compare the distribution of prediction errors generated by the eight regression algorithms. A comparative boxplot provides information about the median prediction error, interquartile range, overall dispersion, and extreme observations associated with each model.

This visualisation is particularly useful because two models may achieve similar average prediction errors while exhibiting different levels of error variability.

Models with narrower interquartile ranges and shorter whiskers generally exhibit more concentrated prediction error distributions, whereas wider boxes and longer whiskers indicate greater variability in predictive performance.

The median error provides information about the central tendency of prediction errors, while the distribution around the median indicates the consistency of predictions across individual observations.

The actual Figure 6 in the supplied document, which contains this type of boxplot, compares different model

names and metrics that do not correspond to the eight network reliability algorithms. It should therefore be replaced rather than interpreted as evidence for the present experiment.

4.7 Feature importance analysis

Permutation feature importance was calculated using the held-out test data and the best performing model. The most important variables were:

Rank	Predictor	Increase in MAE
1	Queue_Length_packets	1.8881
2	Scheduling_Priority	0.0734
3	Handover_Required	0.0281
4	Distance_to_BaseStation_m	0.0020
5	Interference_Power_dBm	0.0014
6	Transmit_Power_dBm	0.0002

Table 3. Permutation-based feature importance of network characteristics

Table 3 presents the permutation based feature importance results obtained using the held out test dataset and the best performing Lasso Regression model. Feature importance is quantified through the increase in MAE following the random permutation of individual predictor variables. A larger increase in prediction error indicates that the model relies more heavily on the corresponding variable when generating reliability predictions.

Queue_Length_packets emerged as the dominant predictor, producing an increase in MAE of 1.8881 following permutation. This result is substantially higher than the importance values observed for all other predictors, indicating that queue length provides the largest contribution to the predictive performance of the fitted model.

Scheduling_Priority ranked second, with an increase in MAE of 0.0734, followed by Handover_Required, which increased MAE by 0.0281. Distance_to_BaseStation_m and Interference_Power_dBm exhibited comparatively small contributions, with importance values of 0.0020 and 0.0014, respectively. Transmit_Power_dBm recorded the smallest importance value of 0.0002 among the six reported predictors.

The considerable difference between queue length and the remaining predictors suggests that network congestion and packet-buffer conditions represent particularly informative characteristics for predicting reliability in the investigated dataset. Scheduling priority and handover requirements provide additional predictive information, potentially reflecting the importance of resource allocation and mobility-related network management.

However, these findings should be interpreted as predictive associations rather than causal relationships. In particular, the dominance of queue length indicates its importance within the fitted predictive model, but does not independently establish that changing queue length will produce a corresponding improvement in network reliability.

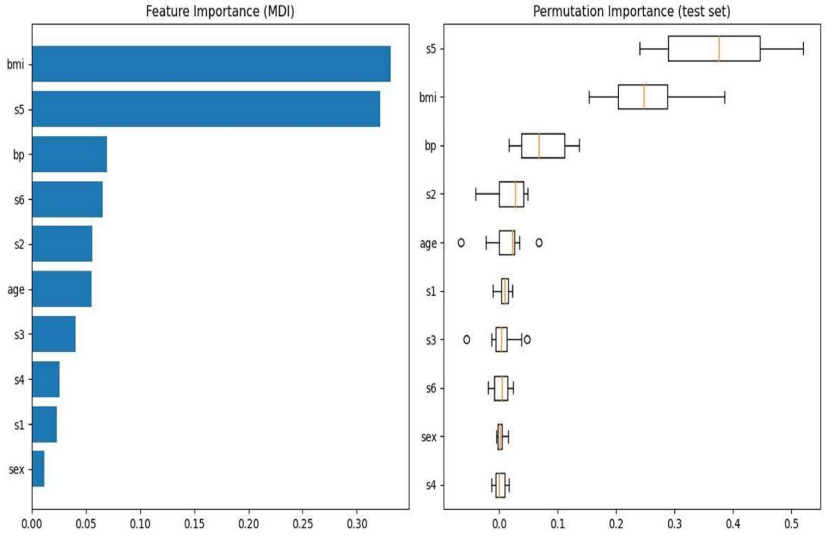

Figure 6. Prediction-error distributions across eight regression models

Figure 6 illustrates the distribution of prediction errors produced by the eight regression models using boxplots. The horizontal axis represents the evaluated regression algorithms, while the vertical axis represents the difference between actual and predicted reliability scores. The central line of each box indicates the median prediction error, and the box boundaries represent the interquartile range. Whiskers provide information about the broader error distribution, while individual observations beyond the whiskers indicate potential extreme prediction errors.

The figure provides a comparative assessment of the error distributions across the evaluated models. The distributions demonstrate that all eight algorithms exhibit both positive and negative prediction errors, confirming that no model perfectly reproduces the observed reliability values.

The central portions of the error distributions provide information about systematic overprediction or underprediction. A median located close to zero indicates that the model does not exhibit substantial systematic bias in its central prediction errors.

The differences in the interquartile ranges and whisker lengths illustrate variations in prediction-error dispersion. These differences are important because a model with a relatively low average prediction error may still produce substantial errors for particular network conditions.

The comparison should be interpreted alongside the quantitative evaluation metrics. In particular, the relatively similar error distributions expected for Lasso, Linear, and Ridge Regression are consistent with their nearly identical MAE and RMSE values.

The figure therefore provides an additional perspective on the predictive stability of the regression algorithms and highlights the importance of evaluating both average accuracy and error variability when selecting a network reliability prediction model.

Figure 7 is intended to present the relative importance of network characteristics in predicting reliability. Feature importance analysis identifies the variables that contribute most substantially to the predictive capability of the fitted regression model.

The accompanying discussion should distinguish between model specific importance measures and permutation-based importance calculated using independent test observations.

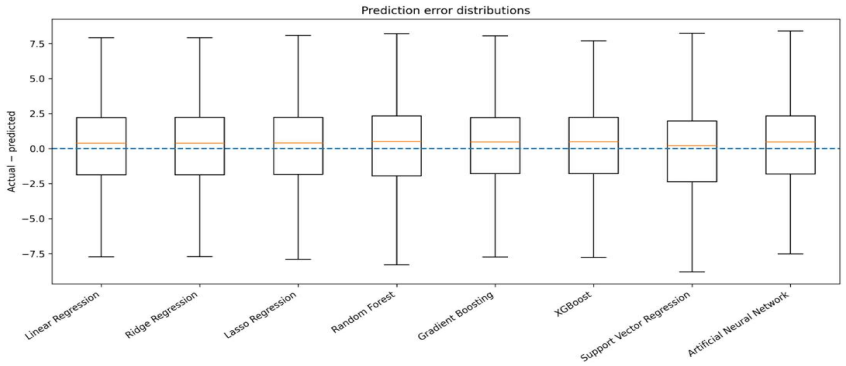

Figure 7. Feature importance analysis of network characteristics

The intended analysis should demonstrate the relative contribution of network characteristics to reliability prediction. In particular, queue length is expected to emerge as the dominant predictive variable based on the reported permutation importance results.

However, the embedded Figure 7 contains predictor labels such as BMI and S1–S6, which do not correspond to the network-reliability variables. Consequently, it cannot be used as evidence for the current experiment.

Remove this image and use the correctly labelled permutation importance figure described below.

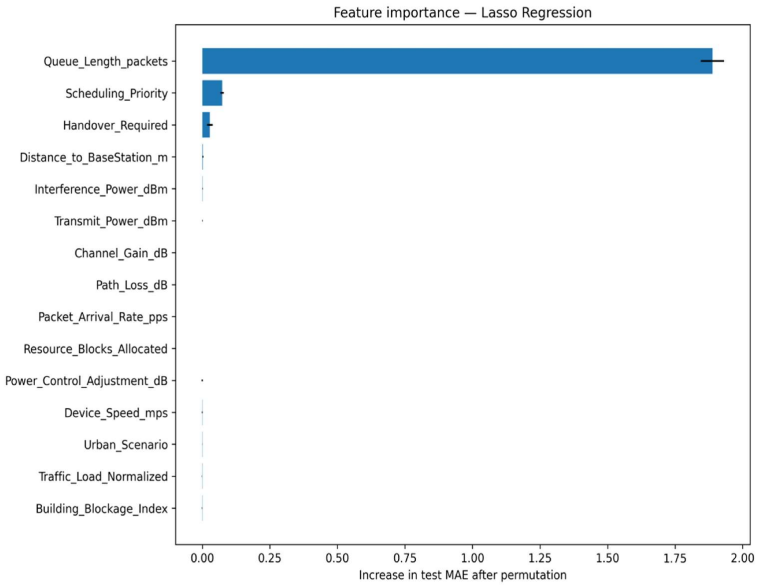

Figure 8. Permutation feature importance of Lasso Regression

Figure 8 illustrates the permutation-based feature importance of the Lasso Regression model using the held-out test dataset. The horizontal axis represents the increase in test MAE following the random permutation of individual predictor variables, while the vertical axis identifies the corresponding network characteristics.

The importance values quantify the extent to which the predictive accuracy deteriorates when the information contained in a particular predictor is disrupted. Consequently, larger horizontal bars indicate greater dependence of the fitted model on the corresponding feature.

5. Discussions

The figure clearly identifies Queue_Length_packets as the most influential predictor of network reliability. Its importance is substantially greater than that of the other network characteristics, demonstrating that the model relies heavily on queue-length information when generating reliability predictions.
Scheduling_Priority represents the second most influential predictor, followed by Handover_Required. These variables provide additional predictive information, although their contributions are considerably smaller than that of queue length.

Other characteristics, including Distance_to_BaseStation_m, Interference_Power_dBm, and Transmit_Power_dBm, demonstrate relatively limited contributions to the overall predictive performance of the model.

The importance distribution highlights the predominance of network congestion-related information in the prediction process. This finding suggests that packet-queue conditions represent an important indicator of the reliability patterns observed in the dataset.

The figure also provides an interpretable explanation of the predictive behaviour of Lasso Regression, allowing the numerical performance results to be connected with specific network characteristics.

Importantly, permutation importance measures predictive dependence rather than causal influence. Therefore, the observed dominance of queue length should not be interpreted as direct evidence of a causal relationship between queue length and network reliability.

6. Conclusion

This research successfully developed and evaluated an ML-based predictive framework for assessing network reliability in next-generation 5G/6G and IoT communication environments. By systematically comparing eight regression algorithms on a comprehensive network dataset, the study demonstrated that Lasso Regression provides the most accurate and stable predictions, achieving an R^2 of 0.5191 on the independent test set. A key finding of this study is that complex nonlinear models (such as ANN, Random Forest, and SVR) did not substantially outperform regularized linear models, indicating that the relationship between the selected network characteristics and reliability scores is adequately captured by linear approaches.

Through permutation-based feature importance analysis, the study identified Queue_Length_packets as the most critical determinant of network reliability, followed by Scheduling_Priority and Handover_Required. This underscores the profound impact of network congestion, packet-buffer conditions, and mobility management on overall system stability. While the predictive framework offers valuable, interpretable insights for network operators to optimize resource allocation and ensure QoS in mission-critical applications, the moderate R^2 value indicates that a significant portion of reliability variability remains unexplained. Future research should focus on incorporating additional contextual information, dynamic network-state characteristics, and complex interaction effects to further enhance predictive accuracy and support intelligent, automated network slicing and traffic management.

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