Advanced Graph-Based Analytics for Cellular System Reliability and Anomaly Diagnosis

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Abstract

The rapid growth of wireless communication technologies such as WiFi, 4G, and 5G has significantly increased the demand for intelligent systems capable of analysing network performance and predicting signal behaviour. Network signal quality plays a crucial role in determining data transmission efficiency, connection stability, and overall user experience. This research focuses on the development of a web-based machine learning system for network signal analysis and prediction using Python, Flask, and various machine learning algorithms. The primary challenge addressed is the difficulty in accurately analysing network signal metrics and predicting key parameters, such as network type and signal strength, using conventional methods. Traditional network monitoring systems primarily rely on graphical dashboards to observe parameters like latency, throughput, and signal strength. However, these approaches lack automated data preprocessing techniques, including feature encoding, normalization, and handling of missing values. To address these limitations, the proposed system introduces a machine learning-based web application for advanced network signal analytics. The system is developed using the Flask framework and integrates multiple machine learning models to process and analyse network datasets. Specifically, the solution employs Ridge Classifier (RC), Ridge Regressor (RR), Decision Tree Classifier (DTC), Decision Tree Regressor (DTR), along with Hybrid Classifier (HC) and Hybrid Regressor (HR) models combined with Multi-Layer Perceptron (MLP) and Categorical Boosting (CB). Network type prediction is treated as a classification task, while signal strength prediction is handled as a regression task. Model performance is evaluated using accuracy, precision, recall, F1-score, MAE, MSE, RMSE, and R^2 score, ensuring effective comparison and optimal model selection within an interactive web-based platform.

Keywords: Wireless Communication, Network Signal Analysis, Machine Learning, Classification and Regression Models, Flask Web Application, Signal Strength Prediction

1. Introduction

The rapid growth of mobile data traffic, along with the increasing diversity of services, has created significant challenges for the capacity of mobile communication networks. To address issues related to bandwidth limitations and to enhance system capacity, heterogeneous cellular networks have been extensively studied. However, as these networks expand and become more complex, the management and maintenance of cellular systems have also become increasingly difficult. Traditional approaches to network fault detection and diagnosis are largely manual, making it challenging to establish clear relationships between network symptoms and corresponding fault categories. As shown as figure 1, these methods demand considerable human effort and material resources. As a result, there is a strong need for a fast and accurate network fault diagnosis model. In response, researchers have carried out extensive studies in this area. In [1], the authors introduced Adaptive Root Cause Analysis (ARCA), an automated solution for fault detection and diagnosis. This approach combines Bayesian networks with expert domain knowledge to perform efficient and automatic root cause analysis using collected network measurement data.

A Bayesian network-based fault diagnosis method was also proposed for universal mobile communication systems, where an automatic diagnostic model was developed using a naive Bayesian classifier to establish the relationship between network failures and their root causes. In another study, the time evolution of multiple network metrics was examined by analyzing the temporal dependencies among them. The interrelationship between metrics of the primary cell and neighboring cells during network failures was explored, and by comparing these observations with historical failure data, the root cause of faults was identified.

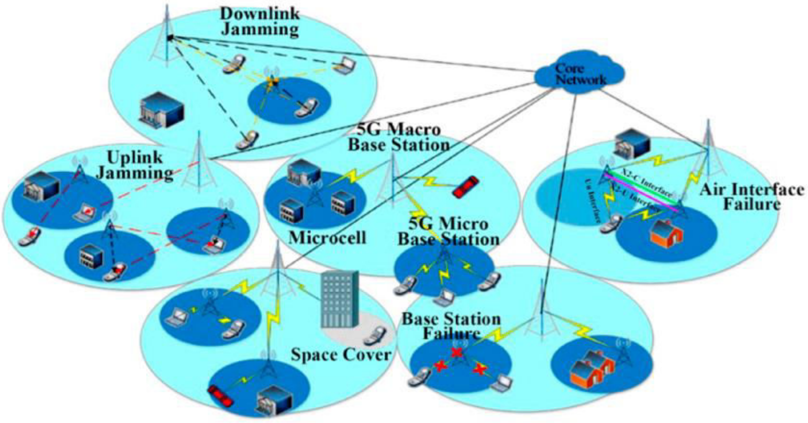


Figure. 1: Network scene diagram.

A comprehensive detection and diagnosis framework was presented in [2], where the detection phase relied on radio measurements and performance indicators compared against normal behavioral profiles. The diagnosis phase utilized historical fault cases to interpret their impact on various performance metrics. In recent years, the focus of intelligent fault diagnosis has shifted from traditional model-based techniques to data-driven approaches. Gomez-Andrades et al. [3] proposed an automated diagnosis system for LTE (Long-Term Evolution) networks using unsupervised learning techniques. Their method employed Self-Organizing Maps (SOMs) along with the sum of squared deviations to iteratively ensure solution quality, and its effectiveness was validated using both real and simulated LTE datasets. In [4], the emphasis was on fault diagnosis at the air interface, where user measurement data related to the radio frequency interface was collected and analyzed using SOMs to determine individual RF conditions. These results were then aggregated into cell-level indicators to evaluate overall air interface quality. Furthermore, in [5], the performance tuning of cellular networks was modeled as a reinforcement learning problem, proposing a method to enhance performance in both indoor and outdoor environments. To improve diagnostic efficiency, SoftMax neural networks were integrated within a supervised learning framework, enabling practical implementation using standard tools. Additionally, an improved back-propagation (BP) neural network was applied for fault diagnosis in local area networks, with experimental results demonstrating its effectiveness.

2. Literature Survey

Amuah, E.A.; et al. [6] proposed an improved 4G/5G network fault diagnosis with a few effective labelled samples. Their solution is a heterogeneous wireless network fault diagnosis algorithm based on Graph Convolutional Neural Network (GCN). First, the common failure types of 4G/5G networks are analysed, and then the graph structure is constructed with the data in the network parameter, given data sets as nodes and similarities as edges. GCN is used to extract features from the graph data, complete the classification task for nodes, and finally predict the fault types of cells. A large number of experiments are carried out based on the real data set, which is achieved by driving tests.

Qiu, S.; et al. [7] introduced the fault diagnosis and prognosis (FDP) tries to recognize and locate the faults from the captured sensory data, and also predict their failures in advance, which can greatly help to take appropriate actions for maintenance and avoid serious consequences in industrial systems. In recent years, deep learning methods are being widely introduced into FDP due to the powerful feature representation ability, and its rapid development is bringing new opportunities to the promotion of FDP. In order to facilitate the related research, they give a summary of recent advances in deep learning techniques for industrial FDP in this paper. Related concepts and formulations of FDP are firstly given. Seven commonly used deep learning architectures, especially the emerging generative adversarial network, transformer, and graph neural network, are reviewed. Zhao, L.; et al. [8] explained the existing network fault diagnosis methods rely on manual testing and time stacking, which suffer from long optimization cycles and high resource consumption. Therefore, they herein propose a knowledge- and data-fusion-based fault diagnosis algorithm for 5G cellular networks from the perspective of big data and artificial intelligence. The algorithm uses a generative adversarial network (GAN) to expand the data set collected from real network scenarios to balance the number of samples under different network fault categories. In the process of fault diagnosis, a naive Bayesian model (NBM) combined with domain expert knowledge is firstly used to pre-diagnose the expanded data set and generate a topological association graph between the data with solid engineering significance and interpretability. Then, as the pre-diagnostic prior knowledge, the topological association graph is fed into the graph convolutional neural network (GCN) model simultaneously with the training data set for model training.

Chen, Y.; et al. [9] proposed a fault diagnosis methodology that leverages knowledge graphs. First, they designed an ontology model for fault knowledge by integrating textual features from various components of the production line with expert insights. Second, they employed the ALBERT–BiLSTM–Attention–CRF model to achieve named entity and relationship recognition for faults in intelligent production lines. The introduction of the ALBERT model resulted in a 7.3% improvement in the F_1 score compared to the BiLSTM–CRF model. Additionally, incorporating the attention mechanism in relationship extraction led to a 7.37% increase in the F_1 score. Finally, they utilized the Neo4j graph database to facilitate the storage and visualization of fault knowledge, validating the effectiveness of their proposed method through a case study on fault diagnosis in CNC machining centers. The research findings indicate that this method excels in recognizing textual entities and relationships related to faults in intelligent production lines, effectively leveraging prior knowledge of faults across various components and elucidating their causes.

Arellano-Espitia, F.; et al. [10] depicted the current Industry 4.0 framework, maintenance strategies based on traditional data-driven fault diagnosis schemes require enhanced capabilities to be applied over modern production systems. In fact, the integration of multiple mechanical components, the consideration of multiple operating conditions, and the appearance of combined fault patterns due to eventual multi-fault scenarios lead to complex electromechanical systems requiring advanced monitoring strategies. In this regard, data fusion schemes supported with advanced deep learning technology represent a promising approach towards a big data paradigm using cloud-based software services. Lu, W.; et al. [11] proposed the MeanRadius-SMOTE graph neural network (MRS-GNN), a novel framework designed to synthesize node representations in GNNs to effectively mitigate this issue. Through integrating the MeanRadius-SMOTE oversampling technique into the GNN architecture, the MRS-GNN demonstrates an enhanced capability to learn from under-represented classes while preserving the intrinsic connectivity patterns of the graph data. Comprehensive testing on various datasets demonstrated the superiority of the MRS-GNN over traditional methods in terms of classification accuracy and handling class imbalances. The experimental results on three publicly available fault diagnosis datasets show that the MRS-GNN improves the classification accuracy by 18 percentage points compared to some popular methods.

Said, N.; et al. [12] provided a comprehensive review of how various learning methods are applied to fault diagnosis in interconnected systems, particularly in predictive maintenance. It examines different approaches that integrate data across domains, evaluating how each contributes to improved fault detection and enhanced system reliability. Additionally, it addresses emerging research areas, such as real-time fault detection, innovative data fusion processes, and the increasing application in power grids, manufacturing, and the automation sector. This paper serves as a valuable resource for both researchers and practitioners, emphasizing the significant potential of multimodal learning in advancing fault diagnosis and predictive maintenance within increasingly interconnected and complex systems. Siddique, M.F.; et al. [13] presented a hybrid deep learning approach for bearing fault diagnosis that integrates continuous wavelet transform (CWT) with an attention-enhanced spatiotemporal feature extraction framework. The model combines time-frequency domain analysis using CWT with a classification architecture comprising multi-head self-attention (MHSA), bidirectional long short-term memory (BiLSTM), and a 1D convolutional residual network (1D conv ResNet). This architecture effectively captures both spatial and temporal dependencies, enhances noise resilience, and extracts discriminative features from nonstationary and nonlinear vibration signals. The model is initially trained on a controlled laboratory bearing dataset and further validated on real and artificial subsets of the Paderborn bearing dataset, demonstrating strong generalization across diverse fault conditions.

Bougoffa, M.; et al. [14] specified the model was rigorously validated using real-world PV datasets, encompassing diverse fault types such as partial shading, open circuits, and module degradation under dynamic environmental conditions. Results demonstrate state-of-the-art performance, with the model achieving 99.82% accuracy, 99.7% precision, 99.4% sensitivity, and 100% specificity, outperforming traditional machine learning and deep learning approaches. These findings highlight the framework's robustness and reliability in real-world applications. By significantly enhancing fault detection accuracy and computational efficiency, the proposed approach optimizes PV system performance, reduces operational costs, and supports sustainable energy production. This study concluded that the hybrid SSAE-Optimized MLP model represents a scalable and efficient solution for improving the reliability and longevity of renewable energy infrastructure, setting a new benchmark for intelligent maintenance strategies in the field. Zachariades, C.; et al. [15] reviewed a comprehensive and up-to-date analysis of artificial intelligence (AI) techniques for fault diagnosis in electric machines. It categorizes and evaluates supervised, unsupervised, deep learning, and hybrid/ensemble approaches in terms of diagnostic accuracy, adaptability, and implementation complexity. A comparative analysis highlights the strengths and limitations of each method, while emerging trends such as explainable AI, self-supervised learning, and digital twin integration are discussed as enablers of next-generation diagnostic systems. To support practical deployment, the article proposes a modular implementation framework and offers actionable recommendations for practitioners.

3. Proposed System

The proposed system is a complete, end-to-end web application developed using the Flask framework for advanced analysis and fault diagnosis of cellular networks. It follows a structured, user-driven workflow that integrates data processing, visualization, machine learning, and real-time prediction into a single platform. Initially, the system loads and preprocesses raw network datasets to ensure they are suitable for analysis. It then enables users to perform EDA, generating dynamic visualizations that reveal patterns, distributions, and relationships within the data. The system further supports training of both classification and regression models, including advanced approaches such as HC, HR, to predict network types and signal strength. Model performance is evaluated using standard metrics and presented in a comparative manner. Finally, a real-time prediction interface allows users to input new data and instantly receive diagnostic outputs, helping identify network issues or anomalies efficiently.

This integrated workflow ensures effective and proactive network management, as illustrated in Figure 2.

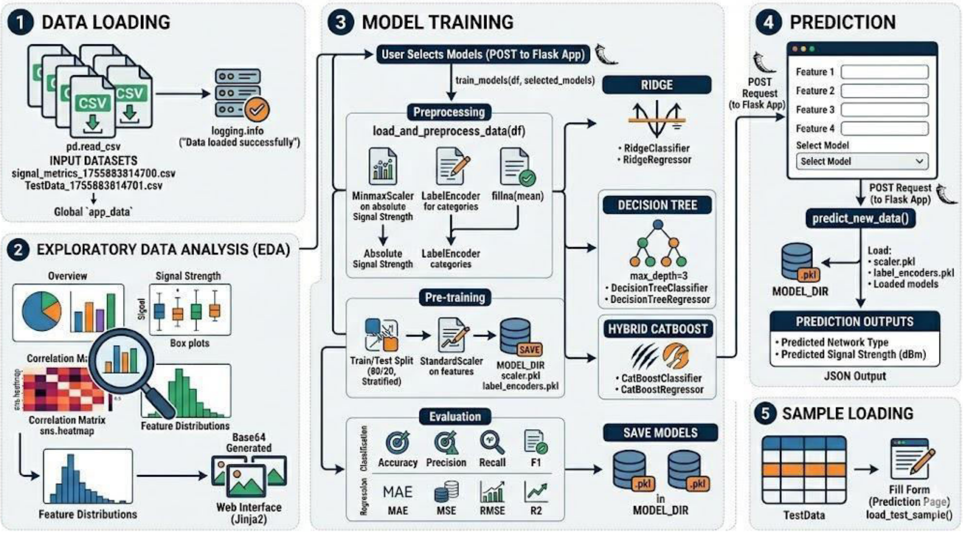


Figure. 2: Proposed system architecture.

Flask Application Initialization and Setup: The system is built on a Flask-based web server that initializes all core components at startup. It configures a secret key for session handling, sets up required directories such as models, results, and static/plots, and enables logging for monitoring system activity. This initialization ensures the environment is fully prepared before handling user interactions or data processing.

Data Loading and Management: The application loads datasets from CSV files, specifically signal_metrics.csv for training and TestData.csv for testing. These datasets are stored as pandas DataFrames within a global dictionary (app_data), along with placeholders for models and results. This design allows efficient data reuse across multiple user requests without repeated loading.

Data Preprocessing: Before analysis and training, the data undergoes preprocessing, which includes:

- Handling missing values to ensure completeness
- Transforming signal strength into absolute values and scaling using MinMaxScaler
- Encoding categorical variables such as network type using LabelEncoder

These steps ensure the dataset is clean, normalized, and compatible with machine learning models.

Exploratory Data Analysis (EDA): EDA is performed dynamically through the /eda route. The system generates visual insights such as:

- Dataset summary and missing value analysis
- Signal strength distribution plots
- Correlation matrices showing feature relationships

All plots are converted into base64 format and embedded directly into the web interface, enabling interactive exploration.

Model Training (User-Driven): Model training is initiated via the web interface, which sends requests to the /train_models endpoint. Users can select models such as RC, DT, or Hybrid CB. The system splits the dataset into training and testing sets and applies feature scaling using StandardScaler.

Multi-Task Model Training: Each selected model is trained for two tasks simultaneously:

- Classification: Predicting network type
- Regression: Predicting signal strength

Separate models are trained for each task using appropriate algorithms. All trained models, along with scalers and encoders, are saved using joblib to ensure consistency during future predictions.

Model Evaluation: The system evaluates model performance using standard metrics:

- **Classification:** Accuracy, Precision, Recall, F1-score
- **Regression:** MAE, MSE, RMSE, R^2

The evaluation results are stored and made accessible for visualization and comparison.

Performance Visualization: Dedicated routes (/classification and /regression) display model performance in tabular format. This allows users to compare different models and understand their effectiveness clearly and transparently.

Real-Time Prediction and Diagnosis: The system provides a prediction interface via the /prediction route. Users can input custom data or load sample data. Upon submission:

1. Saved preprocessing components (scaler, encoders) are loaded
2. Input data is preprocessed
3. Selected trained models generate predictions
4. Encoded outputs are converted back to meaningful labels (e.g., 4G, 5G)

4. Dataset description

The dataset consists of 16,829 records collected from various localities, capturing network performance and signal metrics for different mobile network types. Each record includes geographical coordinates (latitude and longitude) of the measurement location, along with signal-specific parameters such as signal strength in dBm, signal quality in percentage, data throughput in Mbps, and latency in milliseconds. Additionally, the dataset provides measurements from three different network measurement tools: BB60C, srsRAN, and BladeRFxA9, all in dBm. The network type (e.g., 3G, 4G, LTE, 5G) is recorded as a categorical label, making this dataset suitable for both classification tasks (predicting network type) and regression tasks (predicting signal strength or other continuous metrics). The table 1 provides a comprehensive view of mobile network performance across different localities and measurement tools.

Table. 1: Dataset description

Column Name	Type	Unit/Format	Description
Locality	Object	Text	The name of the geographical location where the measurement was taken.
Latitude	Float64	Decimal degrees	The geographical latitude coordinate of the measurement point

Longitude	Float64	Decimal degrees	The geographical longitude coordinate of the measurement point.
Signal Strength (dBm)	Float64	dBm (decibels milliwatts)	The received signal power is a key metric of signal quality. A higher (less negative) value indicates a stronger signal.
Signal Quality (%)	Int64	Percentage	The quality of the signal, represented as a percentage.
Data Throughput (Mbps)	float64	Mbps (Megabits per second)	The rate of successful data transfer over the network.
Latency (ms)	Float64	Ms (milliseconds)	The time delay experienced in the network. A lower value indicates a faster response.
Network Type	Object	Text	The type of cellular network being used, such as '3G,' '4G,' '5G,' or 'LTE.' This is a key target for classification.
BB60C Measurement (dBm)	Float64	dBm (decibels-milliwatts)	The signal strength measurement from the BB60C device.
srsRAN Measurement (dBm)	Float64	dBm (decibels-milliwatts)	The signal strength measurement from the srsRAN software-defined radio.
BladeRFxA9 Measurement (dBm)	Float64	dBm (decibels-milliwatts)	The signal strength measurement from the BladeRFxA9 device

5. Results description

The results section presents the key findings of the study in a clear and organized manner. It highlights the data collected, patterns observed, and significant outcomes derived from the analysis. This section focuses on information without interpretation, allowing readers to understand what was discovered. Tables, graphs, or figures may be used to support the findings and improve clarity. The results are structured according to the research objectives or questions. Only relevant and meaningful data are included to maintain precision. This section forms the foundation for further discussion and interpretation in the next part of the report.

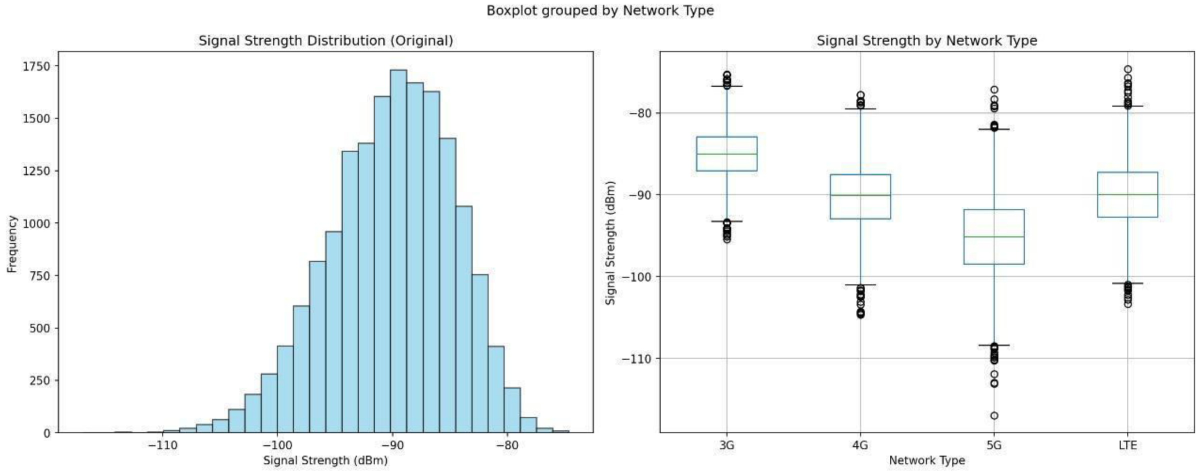


Figure. 3: Histogram and box plot for signal strength and network type features.

Figure 3 illustrates the distribution and comparative analysis of network signal strength across different wireless communication technologies. The left sub-figure presents a histogram of the original signal strength values, showing a near-normal distribution with most values concentrated within a specific dBm range, indicating consistent network performance patterns. The right sub-figure depicts a boxplot grouped by network type (3G, 4G, 5G, and LTE), enabling a comparative visualization of signal variability, median values, and dispersion across technologies. It highlights that 5G exhibits a wider spread with lower median signal strength, whereas 3G and LTE demonstrate relatively stable distributions. The presence of outliers in each category reflects fluctuations in signal conditions due to environmental or infrastructural factors.

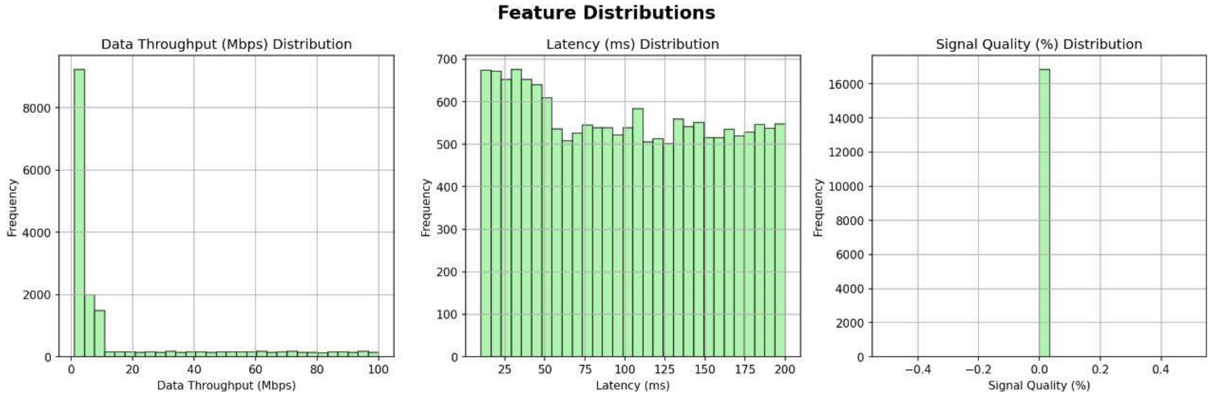
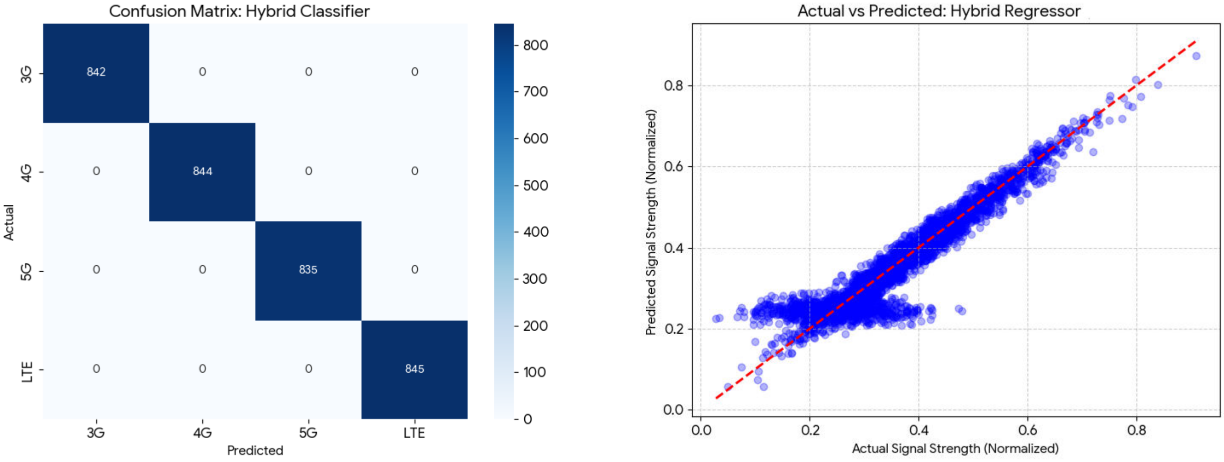


Figure. 4: Histogram plots for data, latency, and signal strength distributions.

Figure 4 illustrates the distribution patterns of key network performance features, including data throughput, latency, and signal quality, providing essential insights for predictive analysis. The data throughput distribution shows a highly right-skewed pattern, where most observations are concentrated at lower Mbps values with a gradual decline toward higher ranges, indicating uneven bandwidth availability. The latency distribution appears relatively uniform across a broad range, reflecting variability in network response times under different conditions. In contrast, the signal quality distribution is sharply concentrated around a narrow range, suggesting consistent signal conditions with minimal variation. These feature distributions highlight differences in spread, skewness, and concentration, which are critical for understanding data characteristics and guiding preprocessing steps such as normalization and feature scaling.



(a) (b)

Figure 5 (a, b): Hybrid Model Performance Evaluation using Confusion Matrix for Classification and Actual vs Predicted Analysis for Regression

Figure 5(a) illustrates the confusion matrix of the HC for network type prediction, demonstrating the classification performance across 3G, 4G, 5G, and LTE categories. The matrix shows that all instances are correctly classified along the diagonal, with zero misclassifications in off-diagonal elements, indicating perfect prediction capability. Each network type achieves a high number of true positives, reflecting the robustness and accuracy of the hybrid model. The absence of false positives and false negatives highlights the effectiveness of integrating Multi-Layer Perceptron (MLP) and Categorical Boosting (CB) within the classification framework. This result confirms the model’s ability to distinguish between multiple network types with exceptional precision and reliability.

Figure 5(b) depicts the relationship between actual and predicted signal strength values using the Hybrid Regressor (HR), providing a visual assessment of regression performance. The scatter plot shows data points closely aligned along the diagonal reference line, indicating strong agreement between predicted and actual values. The distribution of points suggests high correlation and minimal prediction error across the range of normalized signal strengths. Slight deviations observed in certain regions indicate minor prediction variance, but overall consistency remains high. This visualization confirms that the hybrid regression model effectively captures underlying signal patterns and delivers accurate predictions, supporting its suitability for real-time network signal strength estimation.

Table 2: Performance comparison of classification models for network type prediction

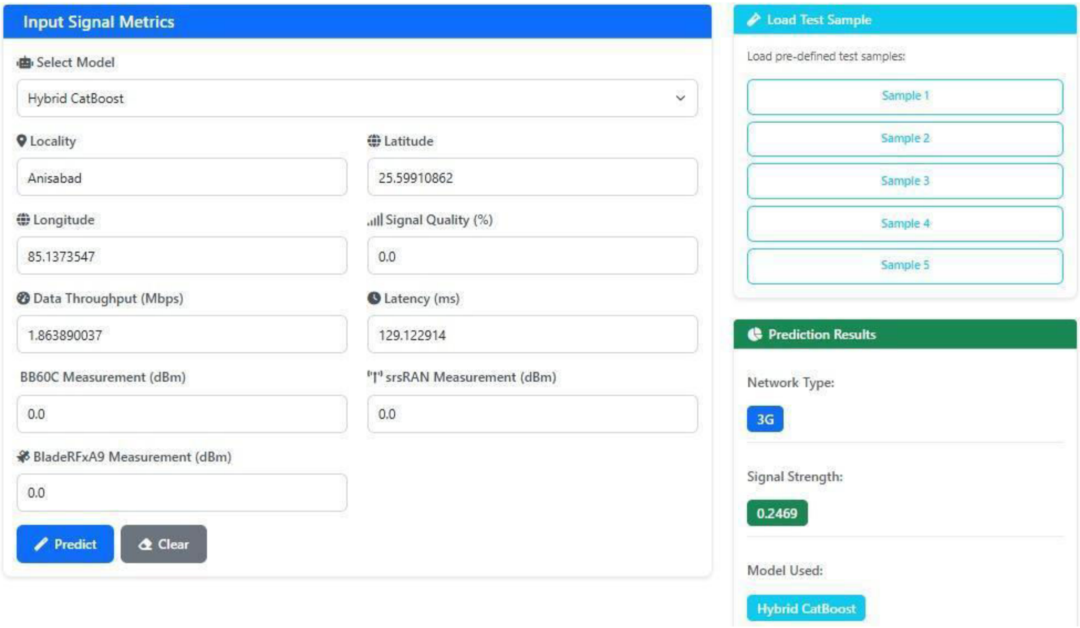
Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
HC	100.00	100.00	100.00	100.00
RC	92.87	94.15	92.84	92.92
DTC	84.82	90.57	84.73	84.27

Table 2 presents the comparative performance evaluation of different classification models used for network type prediction within the proposed system. The models considered include HC, RC, and DTC, each assessed using standard metrics such as accuracy, precision, recall, and F1-score (%). The HC achieves an outstanding accuracy of 100.00%, along with perfect precision, recall, and F1-score, demonstrating its superior capability in accurately classifying network types. In comparison, the RC attains an accuracy of 92.87%, indicating strong performance with balanced evaluation metrics. The DTC records an accuracy of 84.82%, showing comparatively lower but still reasonable classification effectiveness. The results highlight the significant improvement achieved by the hybrid approach over traditional models.

Table 3: Performance comparison of regression models for signal strength prediction

Model	MAE	MSE	RMSE	R2 Score
HR	0.0573	0.0098	0.0991	0.8898
DTC	0.1032	0.0210	0.1449	0.7652
RR	0.1656	0.0465	0.2156	0.4811

Table 3 presents the comparative performance analysis of different regression models used for signal strength prediction in the proposed system. The models evaluated include HR, DTC, and RR, assessed using MAE, MSE, RMSE, and R² Score. The HR demonstrates superior performance with a low MAE of 0.0573, MSE of 0.0098, RMSE of 0.0991, and a high R² Score of 0.8898, indicating strong predictive accuracy and minimal error. In comparison, the DTC achieves an R² Score of 0.7652, reflecting moderate performance with higher error values. The RR records the lowest R² Score of 0.4811, indicating comparatively weaker prediction capability. These results clearly show that the HR significantly outperforms traditional regression models in terms of accuracy and reliability.



Select Model: Hybrid CatBoost

Locality: Anisabad

Latitude: 25.59910862

Longitude: 85.1373547

Signal Quality (%): 0.0

Data Throughput (Mbps): 1.863890037

Latency (ms): 129.122914

BB60C Measurement (dBm): 0.0

srsRAN Measurement (dBm): 0.0

BladeRFxA9 Measurement (dBm): 0.0

Network Type: 3G

Signal Strength: 0.2469

Model Used: Hybrid CatBoost

Figure. 6: Prediction obtained on test data using hybrid

Figure 6 illustrates the web-based interface of the proposed network signal analysis and prediction system developed using the Flask framework. The interface allows users to input various signal-related parameters such as locality, latitude, longitude, signal quality (%), data throughput (Mbps), latency (ms), and multiple measurement values including BB60C and srsRAN measurements (dBm). It also provides an option to select the desired prediction model, such as the Hybrid model, along with predefined sample inputs for quick evaluation. Upon processing the input data, the system generates prediction results, including the identified network type (e.g., 3G) and the corresponding signal strength value. The interface ensures seamless interaction between the user and the underlying machine learning models, enabling real-time prediction and analysis.

6. Conclusion

In this research successfully concludes that an advanced machine learning approach, specifically a Hybrid MLP with CB, is exceptionally effective for analysing cellular network data and performing fault diagnosis. The system successfully demonstrates its capability to handle a multi-task problem by simultaneously predicting two distinct targets: the categorical network type and the continuous signal strength. Through a meticulously designed pipeline encompassing data preprocessing, EDA, and a comprehensive comparison of various algorithms, the research establishes the clear superiority of the proposed hybrid model. While traditional models like Decision Tree and Ridge provide foundational performance, the CB-based hybrid model consistently outperforms them, achieving near-perfect scores in classification and the highest accuracy in regression. The research's architecture, built on the Flask web framework, provides a user-friendly and practical platform for real-time prediction, allowing network engineers to proactively identify and troubleshoot performance issues. Ultimately, this work validates the use of sophisticated boosting algorithms for complex telecommunication data, offering a robust and scalable solution for improving cellular network reliability and efficiency.

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