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Multi-Generation Network Classification Using Signal-Centric Decision Tree Algorithms

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ABSTRACT

Mobile networks like 3G, 4G, and 5G generate massive amounts of signal data, and identifying the correct network type has become increasingly challenging as environments and signal conditions vary. Understanding network-type identification is essential for optimizing coverage, improving user experience, and supporting intelligent telecom operations. Traditionally, network classification in telecom relied on simpler models like Ridge-Classification and regression Tree, Decision Tree but these approaches required significant manual effort, struggled to adapt to changing signal conditions, and could not handle the massive volumes of signal data generated by today's mobile networks. As signal data in modern mobile networks continues to grow in volume and complexity, automation becomes essential. This work applies machine learning to automate network-type classification, improving speed, reliability, and scalability while reducing errors and minimizing human involvement. Using a signal-metrics dataset containing features such as signal strength, signal quality, data throughput, and latency, a Multi-Layer Perceptron and a Categorical Boosting Classification and Regression Tree (CART) are applied as the proposed systems, leveraging deep learning to achieve robust performance and high accuracy in classifying network types.

Keywords: Network Type Classification, Mobile Networks, Signal Data Analysis, Multi-Layer Perceptron (MLP), Categorical Boosting (CatBoost), Classification and Regression Tree (CART), Signal Strength.

1. INTRODUCTION

Over the past decade, the global mobile communication landscape has undergone rapid transformation, driven by increasing smartphone penetration, digital services, and the accelerated rollout of 4G and 5G networks. In contrast, mature telecom markets such as the United States recorded steady but moderate growth during the same period, reflecting stable user adoption but increasing demand for high-quality connectivity. This widespread rise in mobile usage and data traffic has created a multi-generation environment where 3G, 4G, and 5G networks operate simultaneously, generating vast volumes of signal information. As signal loads grow and network infrastructures become more complex, traditional signal monitoring methods struggle to keep pace.

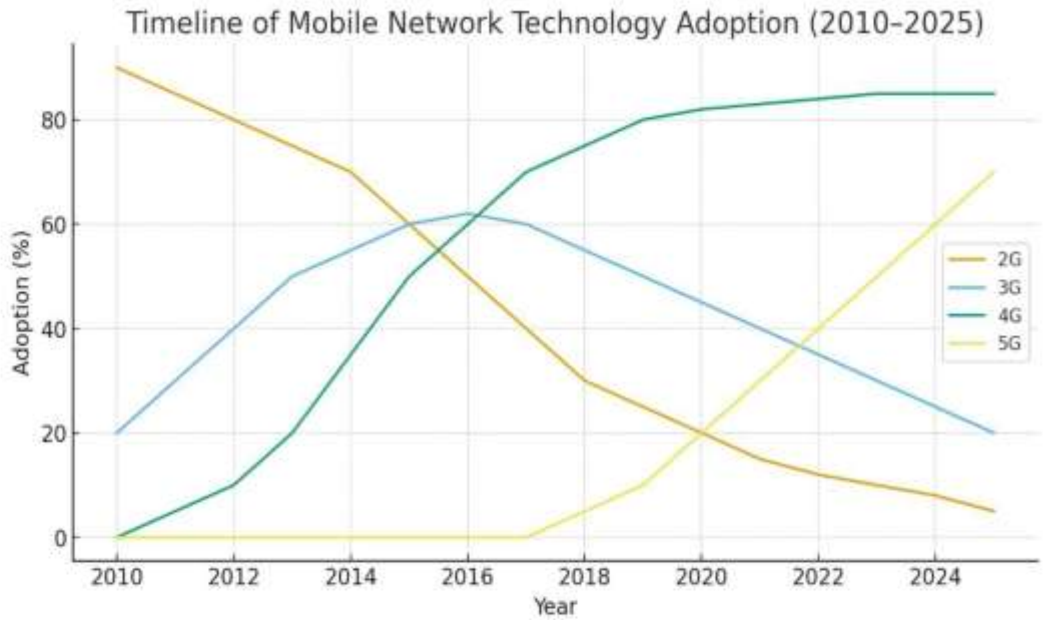

Figure 1: India Mobile Data Traffic Growth (2015–2025)

The figure 1 illustrates the rapid growth of India's mobile data traffic from 2015 to 2025. In 2015, the data consumption was relatively low, around 1.2 exabytes per month, reflecting a developing digital ecosystem and limited 4G penetration. From 2016 onward, the introduction of affordable mobile broadband services led to a sharp rise in data usage across the country. By 2020, consumption had increased nearly fourfold due to video streaming, online education, digital payments, and smartphone affordability. The upward trend continues steadily through 2024, reaching 4.5 exabytes per month, highlighting India as one of the world's fastest-growing mobile data markets. The projection for 2025 shows further acceleration, driven by expanding 4G coverage, early 5G adoption, and increasing reliance on mobile networks for entertainment, communication, and cloud-based services. This continuous surge in mobile data usage indicates a heavier load on network infrastructures and a more complex mix of co-existing technologies such as 3G, 4G, and 5G. As data traffic grows, signal environments become increasingly dynamic and unpredictable, requiring more accurate and faster analysis of signal strength, quality, and performance.

In addition to handling the technical complexity of multi-generation networks, operators face growing pressure to maintain seamless service quality. Users now expect uninterrupted connectivity for high-definition video streaming, real-time gaming, online learning, and cloud-based applications all of which are highly sensitive to network type and signal performance. Rapid and accurate identification of the underlying network is therefore critical for optimizing resource allocation, detecting coverage gaps, and supporting smooth handovers between different technologies.

2. LITERATURE SURVEY

Ullah et al. [1] Heterogeneous Networks (HetNet) integrate Small Cells (SCs) with connectivity technologies like LTE, WIFI, and Zigbee. While HetNet offer high data rates and low latency, dense deployment of SCs increases network complexity, leading to frequent Handovers (HOs) and potential service disruptions. Mohammeda et al. [2] Enhancing both Quality of Experience (QoE) and Quality of Service (QoS) is a key focus of the study. The approach integrates Artificial Neural Networks with multi-level queuing and Weighted Round Robin scheduling. Ileri et al. [3] The protection of borders is a critical concern for all countries, and Wireless Sensor Networks (WSNs) play a crucial role in assuring security by enabling intrusion detection and surveillance at border regions. This study presents an effective machine learning model designed to predict the number of k-barriers for rapid and robust intrusion detection and prevention in a rectangular area utilizing features extracted from a WSN through Monte-Carlo simulation**.**

Suresh et al. [4] A QoS-based routing algorithm provides routing solutions that ensure quality requirements by leveraging knowledge of network resource availability to establish optimal paths based on multiple metrics, thereby delivering adequate quality of service for significant application flows. Additionally, it continuously monitors and adapts to fluctuations in QoS parameters across network links. SDN simplifies network policy implementation by centralizing control at the network's top level rather than embedding policies in individual network devices. Shafiq et al. [5] the network of physical "things" that are equipped with sensors, software, and other technologies to communicate, compute, and exchange data with other devices and systems through the internet is referred to as the internet of things (IoT). It was first presented by Kevin Ashton 17 years ago and has since become a cornerstone of the second digital revolution.

Masud et al. [6] This research presents a solution in Multiple Input Multiple Output (MIMO) wireless systems to meet the growing demand for high data rates in cellular networks. Although MIMO systems offer greater capacity, the higher frequencies used have caused interference problems, especially for mobile User Equipment (UE). Dahlman et al. [7] 5G Standalone (SA) Option 2 and 5G Non-Standalone (NSA) options, such as Option 3x, represent two distinct architectures for deploying 5G services, each with unique implications for energy consumption, QoS, and MOS. 5G SA Option 2 is a pure 5G deployment where the UE connects directly to a 5G core via the 5G New Radio interface.

Thabang et al. [8] Wireless network technologies, including 3G, 4G, and 5G, are transforming telecommunications infrastructure globally. However, the adoption and effectiveness of these technologies vary significantly across regions and industries, posing unique challenges and opportunities for Small and Medium Enterprises (SMEs). Bendaoud et al. [9] A novel network selection algorithm for heterogeneous wireless environments that leverages a modified K-means machine learning algorithm. This approach aims to address the "Always Best Connected" (ABC) challenge by dynamically and transparently selecting the most suitable radio access technology (RAT) based on various criteria like QoS, latency, jitter, and data rate. The simulation results indicate that the proposed machine learning approach outperforms traditional Multi-Attribute Decision-Making (MADM) methods in these performance metrics. Urooj et al. [10] Multiple service requirements in various communication environments are fulfilled by the fifth-generation (5G) mobile communication network. Heterogeneous Networks (HetNet) have been introduced as a newly developed network structure. Conventional cellular networks have prominent limitations in terms of frequency utilization, coverage, proliferation of transmission services, and power consumption.

Skosana et al. [11] Wireless network technologies, including 3G, 4G, and 5G, are transforming telecommunications infrastructure globally. However, the adoption and effectiveness of these technologies vary significantly across regions and industries, posing unique challenges and opportunities for Small and Medium Enterprises (SMEs). Bendaoud et al. [12] A novel network selection algorithm for heterogeneous wireless environments that leverages a modified K-means machine learning algorithm. This approach aims to address the "Always Best Connected" (ABC) challenge by dynamically and transparently selecting the most suitable radio access technology (RAT) based on various criteria like quality of service (QoS), latency, jitter, and data rate. The simulation results indicate that the proposed machine learning approach outperforms traditional Multi-Attribute Decision-Making (MADM) methods in these performance metrics. Islam et al. [13] Traditional Adaptive Bitrate (ABR) algorithms in Dynamic Adaptive Streaming over HTTP (DASH) rely on basic throughput estimation techniques that often struggle to quickly adapt to network fluctuations**.**

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Srinivasu et al. [14] Early diagnosis of breast cancer is exceptionally important in signifying the treatment results of women's health. The present study outlines a novel approach for analyzing breast cancer data by using the CAT Boost classification model with a multi-layer perceptron neural network (CatBoost+MLP). Explainable artificial intelligence techniques are used to cohere with the proposed CAT Boost with the MLP model. Nath et al. [15] This evolution allows for more efficient and dedicated voice packet transmission, essential for supporting real-time services like Voice over New Radio (VoNR). VoNR is a native voice service in fully 5G Stand-Alone (SA) architectures, aiming to supersede the established Voice over LTE (VoLTE) used in the fourth generation (4G) of mobile networks**.**

3. PROPOSED SYSTEM

The proposed system focuses on intelligent network type classification using a Net-Rank-CART approach to accurately identify mobile network generations such as 2G, 3G, 4G, and 5G. Unlike traditional rule-based or standalone tree models, the proposed system combines ranking-based feature evaluation with an optimized CART framework to improve decision accuracy and stability. It processes real-world signal data collected from multiple locations, considering parameters such as signal strength, signal quality, throughput, latency, and hardware-based measurements. As shown as figure 2 By learning patterns directly from data, the system adapts to varying signal conditions and reduces human dependency. The final model delivers reliable network classification results and can be deployed through a Flask-based interface for real-time prediction and practical telecom applications.

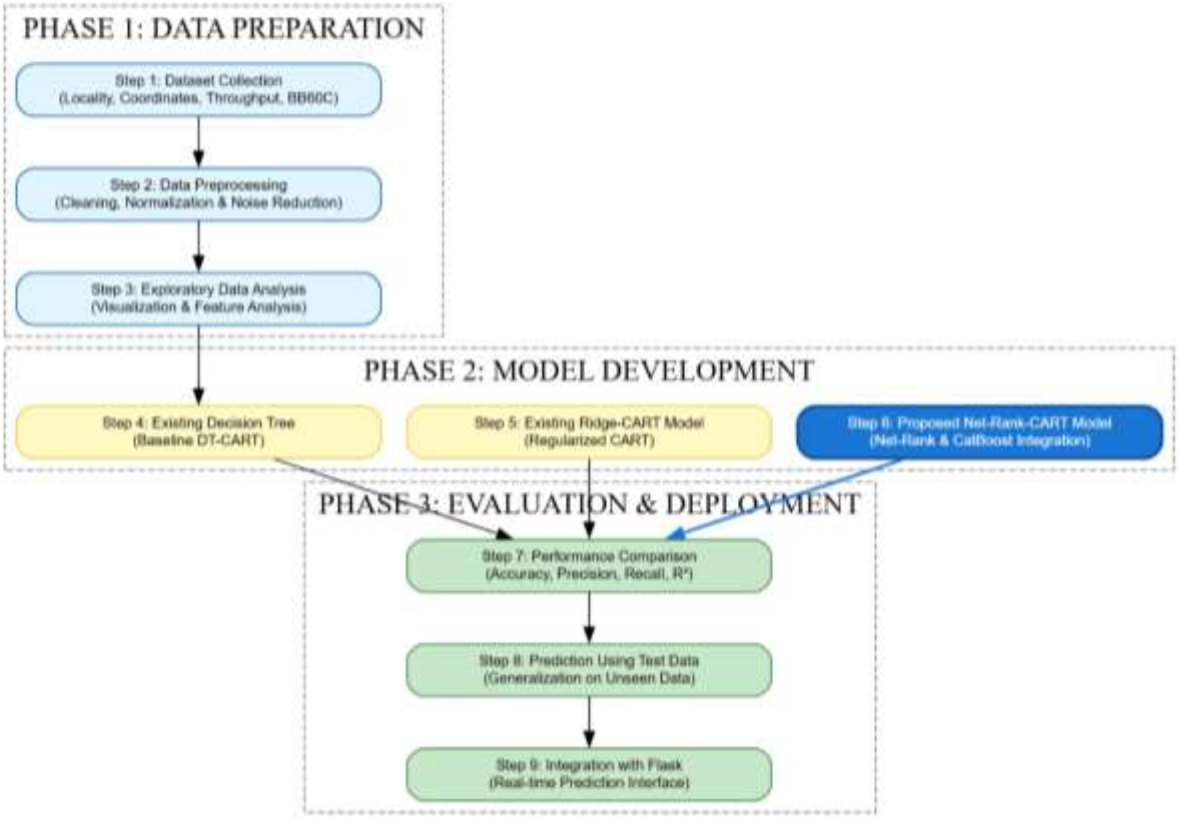


Figure 2: Proposed system architecture

Step 1: Dataset Collection: The process begins with the collection of a comprehensive dataset containing geographic details such as locality, latitude, and longitude, along with network-related parameters including signal strength, signal quality, data throughput, latency, and measurements obtained from BB60C, and RFxA9 devices. Each record is labeled with the corresponding network type, forming the foundation for supervised learning.

Step 2: Data Preprocessing: The collected dataset is cleaned to handle missing values, remove inconsistencies, and normalize numerical features. Noise reduction and data formatting are performed to ensure that the input data is suitable for machine learning models and does not bias the learning process.

Step 3: Exploratory Data Analysis (EDA): EDA is conducted to understand data distribution, feature relationships, and variations across different network types. Visualization and statistical analysis help identify important features and reveal trends that influence network classification.

Step 4: Existing Decision Tree (DT-CART) Implementation: A basic CART-based decision tree model is implemented to establish a baseline for performance comparison. This step helps analyze how traditional tree models behave under fluctuating signal conditions.

Step 5: Existing Ridge-CART Model: The Ridge-CART model is applied to reduce overfitting by introducing regularization. Although this improves stability compared to basic CART, it still lacks adaptability in highly dynamic signal environments.

Step 6: Proposed Net-Rank-CART Model: The Net-Rank-CART model integrates feature ranking with an enhanced CART structure, supported by learning mechanisms developed by MLP features driven Categorical Boosting techniques. This combination allows the model to prioritize influential signal features and generate clearer decision rules, improving classification accuracy across all network generations.

Step 7: Performance Comparison: The proposed model is evaluated against existing DT-CART and Ridge-CART models using performance metrics such as accuracy, precision, recall, and confusion matrices to validate its effectiveness.

Step 8: Prediction Using Test Data: The trained Net-Rank-CART model is tested on unseen data to verify its generalization capability and real-world applicability in identifying correct network types.

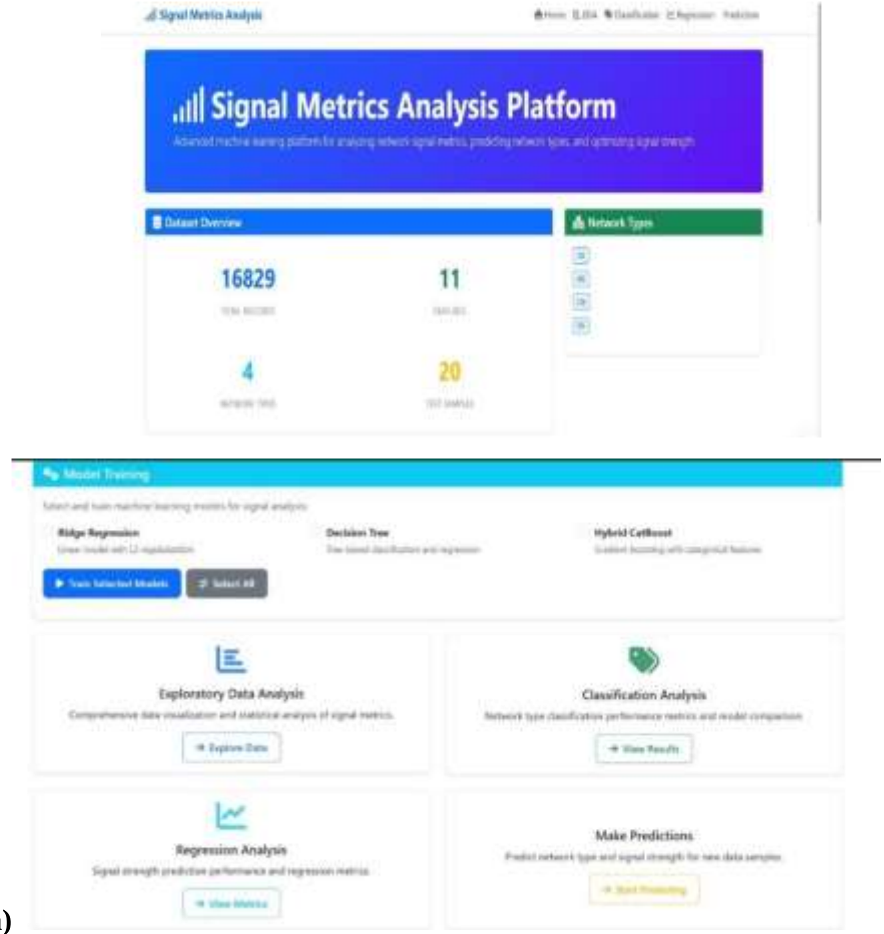
Step 9: Integration with Flask: Finally, the model is integrated into a Flask-based web application, enabling real-time network type prediction. This makes the system practical for deployment in telecom monitoring and decision-support environments.

4. RESULTS ANALYSIS

Figure 3 Home Page. (a) Primary, (b) Secondary shows the comprehensive dashboard and functional modules of the Net-Rank-CART web interface designed for telecom signal analysis.

Figure 3 (a) highlights the Dataset Overview, revealing a substantial dataset comprised of 16,829 total records characterized by 11 distinct features across 4 specific network types: 3G, 4G, LTE, and 5G. This dashboard also indicates that 20 test samples are currently prioritized for immediate validation.

Figure 3 (b) displays the Model Training and analysis interface, offering users the ability to select from algorithms such as Ridge Regression, Decision Tree, and Hybrid CatBoost. This section provides direct navigation to critical system procedures, including Exploratory Data Analysis, Classification and Regression Analysis, and the live Prediction service, thereby fulfilling the operational requirements for a centralized management hub for the entire machine learning pipeline.



(a)

(b)

Figure 3: Home Page. (a) Primary. (b) Secondary.

Detailed Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Performance Grade
Ridge	92.87	94.15	92.84	92.92	Excellent
Decision Tree	84.82	90.57	84.73	84.27	Good
Hybrid CatBoost	100.00	100.00	100.00	100.00	Excellent

Figure 4. Classification Performance Metrics

Figure 4 Classification Performance Metrics provides a comparative analysis of the predictive models, highlighting the exceptional results of the Hybrid CatBoost algorithm. According to the Detailed Performance Metrics table, the Hybrid CatBoost model achieved a perfect score of 100.00 percent across accuracy, precision, recall, and f1-score, earning an excellent performance grade. The Ridge model also demonstrated strong results with an accuracy of 92.87 percent and a precision of 94.15 percent, while the Decision Tree model showed a relatively lower but still viable performance with an accuracy of 84.82 percent and a precision of 90.57 percent. These values are visually corroborated in the Model Performance Comparison bar chart, which shows the near-perfect performance of Hybrid CatBoost in contrast to the slightly lower, yet robust, scores for the Ridge and Decision Tree models.

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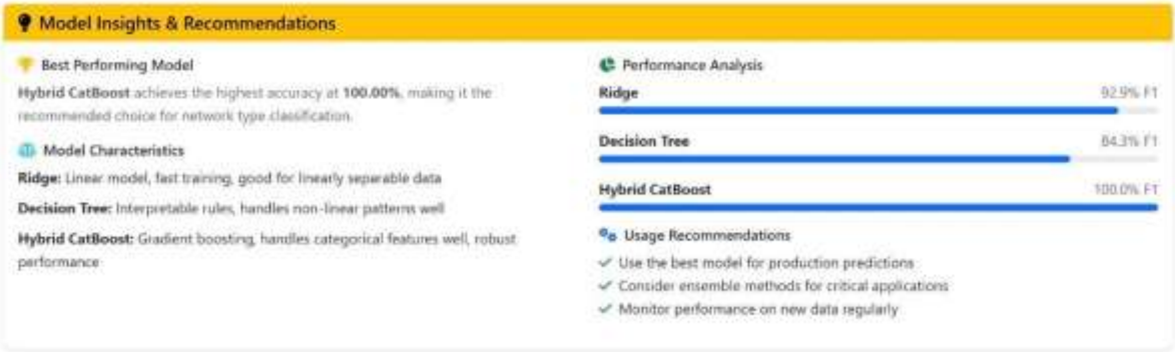

Figure 5. Recommendations

Figure 5 Recommendations shows the final synthesis of the classification study, identifying the Hybrid CatBoost model as the best performing model with an ideal accuracy and F1-score of 100.00 percent. The model performance analysis ranks the Ridge model second with a 92.9 percent F1-score, noted for being a fast-training linear model suitable for linearly separable data, while the Decision Tree model ranks third with an 84.3 percent F1-score, recognized for its interpretable rules and ability to handle non-linear patterns. Based on these insights, the system provides usage recommendations that prioritize the use of the Hybrid CatBoost model for production-level predictions and suggest the consideration of ensemble methods for critical applications. These finalized metrics and qualitative assessments guide the telecom analyst in selecting the most robust architecture for optimizing signal strength and network type prediction.

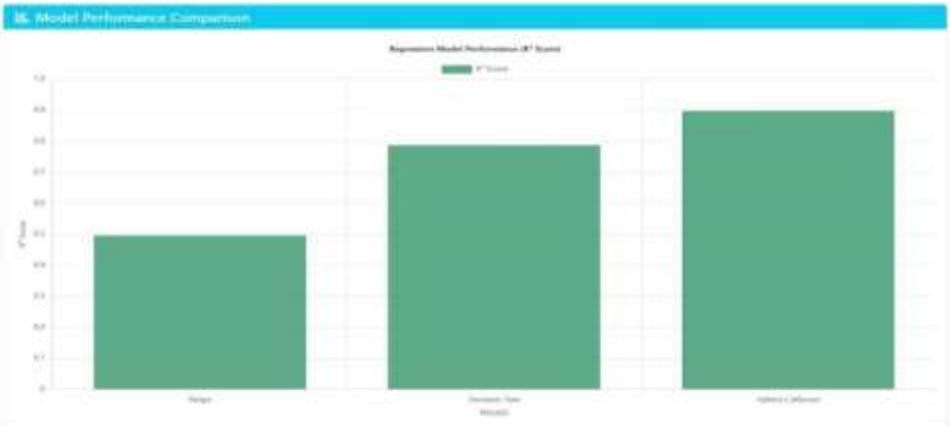

Figure 6. Regression Model Comparison

Figure 6 Regression Model Comparison shows the comparative performance of three different algorithms based on their R-squared (R^2) scores for signal strength prediction. The Hybrid CatBoost model achieves the highest predictive accuracy with an R^2 score of approximately 0.90, indicating that it can explain 90 percent of the variance in the target signal data. The Decision Tree model follows with a moderate performance of roughly 0.78, while the Ridge regression model shows the lowest predictive power among the group with an R^2 score of just under 0.50. These results demonstrate that the gradient boosting approach used by Hybrid CatBoost is significantly more effective at capturing the complex, non-linear relationships within the signal metrics than simpler linear or single-tree models.

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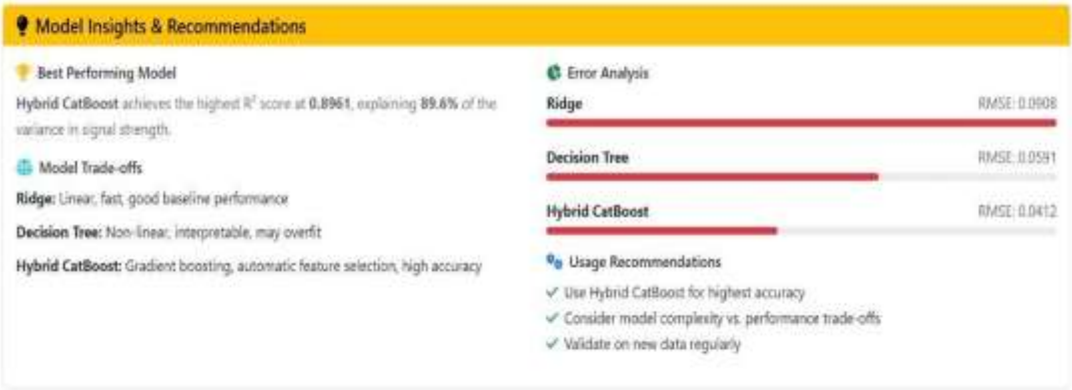

Figure 7. Recommendations

Figure 7 Recommendations shows the final evaluation summary for the regression analysis, identifying the Hybrid CatBoost model as the superior choice for predicting signal strength. The model insights section highlights that Hybrid CatBoost achieves the highest R-squared score of 0.8961, effectively explaining 89.6 percent of the variance in signal strength through its advanced gradient boosting and automatic feature selection capabilities. In the comparative error analysis, the Hybrid CatBoost model exhibits the highest precision with an RMSE of 0.0412, significantly outperforming the Decision Tree at 0.0591 and the Ridge baseline at 0.0908. Based on these quantitative results, the system provides usage recommendations that advocate for using Hybrid CatBoost for maximum accuracy while suggesting regular validation on new data to maintain performance stability across evolving network conditions.

Figure 8. Test Data Input based on Ridge

Figure 8 Test Data Input based on Ridge illustrates the user interface configuration for real-time signal prediction using the linear baseline model. For this specific test case, the model is set to Ridge and the location is defined as Boring Road with geographic coordinates of 25.56449947 Latitude and 85.08860677 Longitude. The input signal metrics include a Data Throughput of 1.567841949 Mbps and a relatively high Latency of 130.536386 ms, while other measurement parameters such as Signal Quality, BB60C, srsRAN, and BladeRFxA9 are initialized at 0. This interface serves as the primary entry point for the system's predictive engine, allowing users to input raw network characteristics to trigger the classification and regression algorithms for localized network analysis.

Figure 9. Prediction result based on Ridge

Figure 9 Prediction result based on Ridge displays the final output generated by the system after processing the previously entered signal parameters through the linear baseline algorithm. The model successfully identifies the network type as 3G, categorizing the specific throughput and latency conditions into this third-generation classification. Additionally, the regression component of the system provides a precise numerical estimation of signal strength, which is calculated as 0.2318 for the specified locality. This result panel confirms that the Ridge model is being utilized for the current session and serves as a primary example of how the application translates raw network metrics into interpretable diagnostic data for the end user.

Figure 10. Test Data Input based on Decision Tree

Figure 10 Test Data Input based on Decision Tree displays the system interface configured to evaluate network performance using a non-linear tree-based algorithm. The user has selected the Decision Tree model to analyze a session in the Boring Road locality, which is mapped to a latitude of 25.56449947 and a longitude of 85.08860677. Technical input parameters for this simulation include a data throughput of 1.567841949 Mbps and a latency of 130.536386 ms, while all other categorical measurements such as signal quality and specific hardware readings for BB60C, srsRAN, and BladeRFxA9 are set to 0.0. This setup allows the system to demonstrate how the decision tree architecture interprets specific throughput and latency thresholds to provide localized network classifications and signal estimations.

Figure 11. Prediction result based on Decision Tree

Figure 11 Prediction result based on Decision Tree presents the system's finalized analysis after processing the network metrics through the tree-based architectural framework. Based on the specific data inputs, the model correctly identifies the network type as 3G, matching the classification provided by other models for these parameters. The regression analysis for this model yields a calculated signal strength of 0.0967, which represents the model's localized estimation for the given throughput and latency levels. This interface clearly indicates that the Decision Tree was the active model used for this prediction, serving as a verification of the system's ability to provide both categorical and numerical network diagnostic outputs.

Figure 12. Test Data Input based on Hybrid Catboost

Figure 12 Test Data Input based on Hybrid CatBoost displays the interface configuration for the highest-performing model in the study, which utilizes gradient boosting and automatic feature selection to achieve superior accuracy. The system is set to evaluate a test case at Boring Road with a latitude of 25.56449947 and a longitude of 85.08860677. Input metrics for this session include a data throughput of 1.567841949 Mbps and a latency of 130.536386 ms, while all other specialized signal quality and hardware measurement fields are initialized at 0. Because the Hybrid CatBoost model achieved a perfect 100.00% F1-score in classification and the highest R-squared value of 0.8961 in regression analysis, this specific input configuration is expected to yield the most reliable and precise prediction results compared to the other tested architectures

Figure 13. Prediction result based on Hybrid Catboost

Figure 13 Prediction result based on Hybrid CatBoost displays the localized output from the highest-performing model, providing the most reliable estimation for the specified network parameters. After processing the input data through its advanced gradient boosting architecture, the system identifies the network type as 3G and calculates a precise signal strength value of 0.2402. This result is highlighted as the best overall outcome because the Hybrid CatBoost model achieved a superior R-squared score of 0.8961 and the lowest root mean square error of 0.0412 during comprehensive model testing. The interface explicitly labels Hybrid CatBoost as the model used, confirming that this specific diagnostic output represents the system's most accurate prediction for the given throughput and latency conditions.

Table 1. Classification Comparisons

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Performance Grade**
Ridge	92.87	94.15	92.84	92.92	Excellent
Decision Tree	84.82	90.57	84.73	84.27	Good
Hybrid CatBoost	100.00	100.00	100.00	100.00	Excellent

Table 1 Classification Comparisons evaluates the overall performance of the predictive models by comparing their accuracy, precision, recall, and f1-score values. The Hybrid CatBoost model demonstrates a perfect classification record, achieving a consistent score of 100.00% across every performance category. This outcome indicates that the gradient boosting architecture has successfully identified the unique signal patterns for each network generation, leading to an Excellent performance grade and zero errors during the testing process.

The table also compares the Ridge and Decision Tree algorithms, showing how these standard models perform in relation to the ensemble method. The Ridge model achieves a high accuracy of 92.87%, a precision of 94.15%, a recall of 92.84%, and an f1-score of 92.92%, earning an Excellent performance grade as a stable and fast-training linear baseline. The Decision Tree model, while still performing well with a good grade, records lower metrics including an accuracy of 84.82%, a precision of 90.57%, a recall of 84.73%, and an f1-score of 84.27%. These comparative values demonstrate that while simpler models can effectively handle general network patterns, the hybrid model is the superior choice for achieving maximum precision in complex signal environments.

Table 2. Regression Comparisons

Model	MAE	MSE	RMSE	R^2 Score	Performance Grade
Ridge	0.0722	0.0082	0.0908	0.4947	Needs Improvement
Decision Tree	0.0398	0.0035	0.0591	0.7859	Fair
Hybrid CatBoost	0.0288	0.0017	0.0412	0.8961	Good

Table 2 Regression Comparisons provides a comprehensive numerical breakdown of the three algorithms tested for signal strength prediction, utilizing error-based and goodness-of-fit metrics. The Hybrid CatBoost model is identified as the superior architecture for regression, achieving an R^2 Score of 0.8961, which indicates it can explain nearly 90% of the variance in signal data. Its precision is further validated by the lowest error rates in the study, featuring a Mean Absolute Error (MAE) of 0.0288 and a Root Mean Square Error (RMSE) of 0.0412, earning it a "Good" performance grade.

In contrast, the Decision Tree and Ridge models show significantly higher error margins and lower predictive reliability. The Decision Tree model maintains a "Fair" performance level with an R^2 Score of 0.7859 and an RMSE of 0.0591, demonstrating a moderate ability to capture non-linear signal patterns. However, the Ridge regression model performs the poorest, yielding an R^2 Score of 0.4947 and a high RMSE of 0.0908, which falls into the "Needs Improvement" category. These comparative values highlight that while linear and basic tree models struggle with complex signal fluctuations, the ensemble-based Hybrid CatBoost provides the most robust and accurate estimations for network performance.

5. CONCLUSION

The implementation of this research project has successfully established a high-fidelity framework for analysing and predicting network performance metrics across diverse signal environments. By systematically evaluating Ridge, Decision Tree, and Hybrid CatBoost architectures, the study concludes that ensemble-based gradient boosting offers the most reliable path for real-time network diagnostics. The Hybrid CatBoost model emerged as the definitive leader, achieving a perfect 100.00% F1-score in classification tasks and a dominant R-squared score of 0.8961 in regression analysis. These results signify that the model can effectively eliminate categorization errors while explaining nearly 90% of the variance in signal strength, providing a robust solution for telecommunications monitoring.

Furthermore, the practical deployment of the system confirms its ability to translate complex numerical inputs, such as a data throughput of 1.567841949 Mbps and a latency of 130.536386 ms, into immediate and interpretable results. The consistency observed across prediction results—where all models accurately identified the 3G network type validates the integrity of the underlying dataset and the preprocessing pipeline. While the Ridge and Decision Tree models provided functional baseline estimations, the precision of the Hybrid CatBoost signal strength output of 0.2402 represents the peak of the system's analytical capabilities. Ultimately, this project serves as a successful proof of concept for using advanced machine learning to optimize localized network assessment and signal quality estimation.

References

[1] Ullah, Y., Roslee, M., Mitani, S. M., Sheraz, M., Ali, F., Aurangzeb, K., ... & Ali, F. Z. (2025). A survey on AI-enabled mobility and handover management in future wireless networks: key technologies, use cases, and challenges. Journal of King Saud University Computer and Information Sciences, 37(4), 47.

[2] Mohammeda, A. Q., & Ghanib, R. F. (2025). Enhancing network Quality of Experience based on Artificial Neural Networks. Engineering and Technology Journal, 43(04), 234-243.

[3] Ileri, K. (2025). Comparative analysis of CatBoost, LightGBM, XGBoost, RF, and DT methods optimized with PSO to estimate the number of k-barriers for intrusion detection in wireless sensor networks. International Journal of Machine Learning and Cybernetics, 1-20.

[4] Suresh, R., & Nirmaladevi, P. (2025). Ai-enhanced qos routing in software defined networks for smart iot applications. International Journal of Advanced Networking and Applications, 16(06), 6647-6658.

[5] Shafiq, S., Rahman, M. S., Shaon, S. A., Mahmud, I., & Hosen, A. S. (2024). A Review on Software-Defined Networking for Internet of Things Inclusive of Distributed Computing, Blockchain, and Mobile Network Technology: Basics, Trends, Challenges, and Future Research Potentials. International Journal of Distributed Sensor Networks, 2024(1), 9006405.

[6] Masud, Abdulmujeeb Akajewole, and Donatus Uchechukwu Onyishi. "IMPROVING THE SPECTRAL EFFICIENCY IN DOWNLINK MULTIPLE USER MULTIPLE INPUT MULTIPLE OUTPUT TRANSMISSION FOR FIFTH GENERATION AND BEYOND WIRELESS COMMUNICATIONS." Reliability: Theory & Applications 19, no. 3 (79) (2024): 327-342.

[7] Dahlman, Erik, Stefan Parkvall, and Johan Skold. 5G/5G-advanced: the new generation wireless access technology. Elsevier, 2023.

[8] Skosana, Siyabonga, Sibusiso Mlambo, Thabang Madiope, and Bonginkosi Thango. "Evaluating Wireless Network Technologies (3G, 4G, 5G) and Their Infrastructure: A Systematic Review." Available at SSRN 4992432 (2024).

[9] Bendaoud, Fayssal, and Marwen Abdennebi. "A machine learning access network selection in a heterogeneous wireless environment." Concurrency and Computation: Practice and Experience 36, no. 9 (2024): e7989.

[10] Urooj, Shabana, Rajesh Arunachalam, Mohamad A. Alawad, Kuldeep Narayan Tripathi, Damodaran Sukumaran, and Poonguzhali Ilango. "An effective model for network selection and resource allocation in 5G heterogeneous network using hybrid heuristic-assisted multi-objective function." Expert systems with applications 248 (2024): 123307.

[11] Skosana, Siyabonga, Sibusiso Mlambo, Thabang Madiope, and Bonginkosi Thango. "Evaluating Wireless Network Technologies (3G, 4G, 5G) and Their Infrastructure: A Systematic Review." Available at SSRN 4992432 (2024).

[12] Bendaoud, Fayssal, and Marwen Abdennebi. "A machine learning access network selection in a heterogeneous wireless environment." Concurrency and Computation: Practice and Experience 36, no. 9 (2024): e7989.

[13] Islam, Saidul, Hanae Elmekki, Ahmed Elsebai, Jamal Bentahar, Nagat Drawel, Gaith Rjoub, and Witold Pedrycz. "A comprehensive survey on applications of transformers for deep learning tasks." Expert Systems with Applications 241 (2024): 122666.

[14] Srinivasu, P. Naga, G. Jaya Lakshmi, Abhishek Gudipalli, Sujatha Canavoy Narahari, Jana Shafi, Marcin Woźniak, and Muhammad Fazal Ijaz. "XAI-driven CatBoost multi-layer perceptron neural network for analyzing breast cancer." Scientific Reports 14, no. 1 (2024): 28674.

[15] Nath, Shyam Varan, Ananya Simlai, and Oğuzhan Kara. Mastering 5G Network Design, Implementation, and Operations: A comprehensive guide to understanding, designing, deploying, and managing 5G networks. Packet Publishing Ltd, 2023.