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Ensemble Supervised Learning-based Approaches for Mobile Network Coverage and Quality Predictions in a University Setting

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Abstract. This research explores the application of predictive analytics through Machine Learning (ML) algorithms to enhance Mobile Network Key Performance Indicators (KPIs), specifically focusing on Reference Signal Received Power (RSRP) as coverage and Reference Signal Received Quality (RSRQ) as quality. Various regression and classification modelling techniques were applied to drive-test measurements collected around the University of Hull, utilizing supervised ML algorithms such as Decision Tree (DT), Logistic Regression (LogisticR), Random Forest (RF), Support Vector Machine/Regressor (SVM/SVR), Light Gradient Boosting Machine (LightGBM), K-Nearest Neighbour (KNN), Extra Trees (ET), Extreme Gradient Boosting (XGB), Multi-Layer Perceptron (MLP), Deep Neural Network (DNN), Gaussian Naïve Bayes (GNB), and Gradient Boosting (GB) to benchmark the performance of four Mobile Network Operators (MNOs)/Mobile Virtual Network Operators (MVNOs) at various locations around the University of Hull, with additional model validation conducted in Hull City Centre, Barton Upon Humber, and Newland as use cases.

The Random Forest (RF) model emerged as the best-performing algorithm, achieving a Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) below 3.7, a Mean Absolute Percentage Error (MAPE) under 7.03, a Coefficient of Determination (R^2) greater than 74%, a Receiver Operating Characteristic Area Under the Curve (ROC_AUC) above 93%, and an Accuracy exceeding 82%. Additionally, the ensemble learning (EL) model, which combined the strengths of RF, GB, ET, SVR, XGB, and LightGBM for regression, and LogisticR, SVM, MLP, GB, ET, and RF for classification, delivered an overall performance with RMSE and MAE below 4, R^2 above 72%, accuracy exceeding 81%, and ROC_AUC above 85%. This highlights the EL model's ability to predict network coverage (RSRP) and quality (RSRQ) as excellent, good, fair, bad, or poor with high precision.

This study demonstrates the uniqueness of integrating multiple KPIs (RSRP and RSRQ) and prediction techniques (regression and classification) within an Artificial Intelligence (AI)-driven solution, providing a robust framework for improving network performance, particularly in scenarios where data collection through drive testing is limited.

Keywords: Artificial Intelligence, Classification, Machine Learning, Reference Signal Received Power, Reference Signal Received Quality, Regression

1 Introduction

Mobile Network Operators (MNOs) and Mobile Virtual Network Operators (MVNOs) worldwide strive to achieve profitability by offering high-quality services to their subscribers. In the UK, for instance, leading MNOs include O2, EE, Three, and Vodafone, while MVNOs like BT Mobile (EE), Lebara (Vodafone), TESCO (O2), giffgaff (O2), and SMARTY (Three) also contribute significantly by utilizing licensed spectrum from MNOs [1]. The University of Hull, a major institution with substantial network traffic, generates high demand for services including voice (Circuit Switch – CS) and data (Packet Switch – PS), such as phone calls, SMS, high-speed internet browsing, 4G/5G video streaming, and fast uploads/downloads. To meet these demands, MNOs and MVNOs invest heavily in maintaining and enhancing their services through infrastructural developments [2], which involve complex and costly planning, optimization, and monitoring of radio frequencies, microwave links, fiber optics, and core networks. For instance, achieving End-to-End Quality of Service (QoS) involves rigorous and expensive drive-test campaigns, live-network performance planning, monitoring, and optimization to ensure optimal signal transmission through base stations.

Given the high costs and complexities involved, integrating a cost-effective Machine Learning (ML) solution can provide valuable insights from the vast amounts of data generated daily by users and connected devices. ML, which involves training models to perform tasks without explicit programming [3], offers significant advantages in telecommunications. By applying ML to predictive analytics, MNOs and MVNOs can enhance planning, monitoring, and optimization processes. Key Performance Indicators (KPIs) such as Reference Signal Received Power (RSRP) for network coverage and Reference Signal Received Quality (RSRQ) for signal quality are crucial for assessing network performance. RSRP, measured in Decibel Meter (dBm) for 4G and 5G, and RSRQ, measured in Decibels (dB), must consistently meet high standards to ensure quality service. Other KPIs, including Signal Interference and Noise Ratio (SINR), Channel Quality Index (CQI), Mean Opinion Score (MOS), Physical Cell Identity (PCI), and E-UTRA Absolute Radio Frequency Channel Number (EARFCN), also play a role in network performance and can be optimized through ML as well.

This research aims to develop a solution to support Mobile Network Planning, Monitoring, and Optimization by predicting Coverage (RSRP) and Quality (RSRQ) at various locations. The study employs robust and well-researched Supervised ML algorithms, including Decision Tree (DT), Logistic Regression (LogisticR), Random Forest (RF), Support Vector Machine/Regressor (SVM/SVR), Light Gradient Boosting Machine (LightGBM), K-Nearest Neighbour (KNN), Extra Trees (ET), Extreme Gradient Boosting (XGB), Multi-Layer Perceptron (MLP), Deep Neural Network (DNN), Gaussian Naïve Bayes (GNB), and Gradient Boosting (GB) in both Regression and Classification models using drive-test measurements.

2 Related Work

The application of AI and ML in predicting mobile network coverage and other KPIs has been explored extensively by researchers globally. Table 1 compares how AI is bridging gaps in telecommunications through ML-based Quality of Service (QoS) predictions.

One study utilized the Light Gradient Boosting Machine (LightGBM) to predict wireless coverage by combining crowd-sourced measurements with Radio Access Network (RAN) configuration parameters. This was compared to Drive-Test measurements and the empirical Okumura-Hata model. Using basic features such as frequency, distance, and antenna height, predictions with Okumura-Hata, Drive-Test interpolation, and LightGBM resulted in Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) exceeding 8.05, and Coefficient of determination (R^2) values below 32%. However, using all available features with LightGBM improved the R^2 to 63% and reduced RMSE, MAE, and MAPE to 7.45 or lower for LTE RSRP predictions [4]. Herath et al. [5] developed an encoder-decoder-based sequence-to-sequence Deep Neural Network (DNN) model incorporating Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) algorithms. This model predicted signal strengths for various networks, including 4G LTE, WiFi, Zigbee, WiMAX, and an industrial network at 5.8 GHz. Results indicated very good predictions (<7 RMSE) for 4G LTE and WiFi networks, while other networks showed RMSE >20.

An Artificial Neural Network (ANN) model was employed to predict ground-level RSRP at Sultan Qaboos University, Oman, using UAV/drone-collected measurements. This model achieved 97% accuracy and 10% Mean Squared Error (MSE) when predicting RSRP across different zones [6]. In another study, Radial Basis Network (RBN), Sigmoid-Based ANN, Multi-Layer Perceptron (MLP), and K-Nearest Neighbour (KNN) were used to predict Signal-to-Interference Ratio (SIR) for wireless coverage maps using simulation data. The RBN, MLP, and KNN models performed well with Absolute Relative Error (ARE) <5.1%, while the ANN with a Sigmoid activation function had ARE >7% [7]. Further research explored six Supervised ML algorithms, including Linear Regression, ANN, Support Vector Machine (SVM), Regression Trees (RT), Ensembles of Trees (EnT), and Gaussian Process Regression (GPR), to predict RSRP in Putrajaya, Malaysia. GPR performed best with RMSE of 5.64 and R^2 of 75% but was computationally expensive. RT, which performed second best with an RMSE of 6.18 and R^2 of 70%, was suggested for deployment after hyperparameter optimization improved its RMSE to 5.74 and R^2 to 74% [8].

Mohammadjafari et al. [9] evaluated RSRP predictions using the Generalized Linear Model (GLM), MLP, KNN, and DNN on simulated datasets. KNN outperformed with MAE <2, while others had MAE values between 2 and 13. In a study on Mobile Network Quality of Experience (QoE) and monitoring, classification algorithms including MLP, C4.5, Random Forest (RF), Naïve Bayes (NB), and SVM were applied to real-life user experiences from YouTube, Facebook, and Google Maps. The predictions achieved over 90% accuracy for C4.5 and RF, over 75% for MLP, and between 40% and 60% for SVM and NB. Binary acceptability predictions also achieved high accuracy, with MLP, C4.5, and RF exceeding 90%, and SVM and NB over 70% [10]. Tomic et al. [11] used Linear Regression, Extreme Gradient Boosting (XGB), and Feed-Forward Neural Network (FFNN) algorithms to predict the Channel Quality Index for a Tier 1 Mobile Network Operator in Belgrade, Serbia. All algorithms showed <6% MAPE, with XGB performing best at 5.51% MAPE.

Table 1. Related Works Comparison with This Research

Article Reference	Location	Dataset Type	Tech	Tool	ML Technique and Algorithm	KPI Prediction	Evaluation Metrics	Results
This Research	Main Study, Use Case 1, Use Case 2, Use Case 3	Real-life Drive-Test Measurements	4G, 5G	G-NetTrack Pro Software, Redmi Note 7, Samsung Galaxy A32 5G, SIM Cards (Lebara/Vodafone, 3, EE, TESCO/O2), Python, HP Laptop	Regression: RF, LGBM, SVR, GB, XGB, KNN, DT, ET, MLP, DNN, Ensemble Classification: LogisticR, SVM, GB, GNB, LGBM, RF, KNN, MLP, DT, ET, Ensemble	RSRP and RSRQ	MAE, MAPE, RMSE, MSE, R^2, Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic Area Under the Curve (ROC_AUC)	**RSRP:** 3.35 RMSE, 11.58 MSE, 2.46 MAE, 2.55% MAPE, 86.9% R^2, 89.61% ROC_AUC, and 87.74% Accuracy 87.74 **RSRQ:** 1.30 RMSE, 1.75 MSE, 0.93 MAE, 7.15% MAPE, 72.63% R^2, 85.62% ROC_AUC, and 81.02% Accuracy
[9]	City Hall, Ottawa	Simulated Radio Propagation	4G	Ray-Tracing Software	Regression: Generalized Linear Models (GLM), MLP, KNN, DNN	RSRP	MAE	<13 (GLM, MLP, DNN), <2 (KNN)
[4]	Crowd-sourced, Ottawa	Crowd-sourced, Drive-Test, Okumura-Hata	4G Long-Term Evolution (LTE)	Sharpley Additive Explanations (SHAP)	Regression: LightGBM	RSRP	MAE, MAPE, RMSE, R^2	<7.45 (RMSE, MAE, MAPE), 0.63 (R^2)
[6]	Sultan Qaboos University, Muscat, Oman	Real-life Flight-Test Measurements	4G LTE	Unmanned Aerial Vehicle/Drone (DJI Matrice 200 V2 quadcopter), G-NetTrack Software, Omantel SIM, Smart Phone	Regression: ANN	RSRP	MSE, Accuracy	97% Accuracy, < 10% MSE
[8]	Putrajaya, Malaysia	Real-life Drive-Test Measurements	4G LTE	CloudRF, G-NetTrack, SIM, Smart Phone, 4G LTE Switcher, MATLAB 2020a, Neural Net Fitting, Laptop	Regression: Linear Regression, ANN, SVM, RT, ET, GPR	RSRP	RMSE, R^2	5.74 RMSE, 0.74 R^2
[7]	Israel	Simulated Radio Propagation	4G LTE	MATLAB	Clustering: Radial Basis Network (RBN) with Gaussian AF, ANN (with Sigmoid AF), MLP, K-NN	SIR	ARE	<5.1% ARE for RBN, MLP, & KNN >=7% & <13% for ANN-Sigmoid
[5]	N/A	Real-life Drive-Test Measurements	4G LTE, WIFI, WiMAX, Industrial Network (at 5.8GHz)	SIM (AT & T, T-Mobile), Motorola G5	Regression: DNN (with LSTM and GRU)	RSRP	RMSE	<7 RMSE for 4G LTE (T-Mobile and AT & T) >20 RMSE for WiMAX, Zigbee, and Industrial Network
[10]	Vienna, Austria	Real-life Drive-Test Measurements & Crowdsourced	2G, EDGE, 3G, LTE	YouTube, Facebook, Google Maps, Passive flow-level traffic monitor, Web-based QoE feedback survey, Weka-ML Software Tool	Classification: MLP, C.45, SVM, RF, NB	MOS and Binary Acceptability (YES/NO)	Global Accuracy, Recall, Precision	MOS - Accuracy >90% (C4.5 & RF), >75% (MLP), >40 & <60 (SVM & NB) Acceptability - Accuracy: >90% (MLP, C4.5 & RF), >70% (SVM & NB)
[11]	N/A	Live Network	LTE, 5G NR	Performance Management System, Laptop	Regression: Linear Regression, XGB, Feed-Forward Neural Network (FFNN)	CQI	MAPE	<6% for LR, XGB, & FFNN

2.1 Advantages and Limitations Compared to Related Works

Pros

a. Multiple Prediction Techniques: This study employs both regression and classification techniques, providing a comprehensive approach to predicting mobile network performance metrics such as Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ). This multi-faceted approach distinguishes it from the studies [4-9, 11] that typically focus on single prediction methods or KPIs.

b. Diverse KPI Predictions: Unlike the referenced studies, which primarily concentrate on RSRP or a limited range of KPIs, this study includes predictions for both RSRP and RSRQ. This broader scope allows for a more complete assessment of network performance.

Cons:

a. Small Data Sizes: One limitation of this study is the relatively small size of the data set, which may affect the generalizability of the results. Larger data sets are often needed to develop more robust and scalable models.

b. Limited Access to Live Network Data: The study's reliance on historical drive-test data rather than real-time live network performance data can limit the applicability and timeliness of the predictions. Real-time data could enhance model accuracy and relevance.

2.2 Benefits and Potential Improvements in Telecommunication Services

a. High Scalability: The study's methodologies are designed to be scalable, allowing for application across various geographic locations and network sizes, which can adapt to different network environments.

b. Fast and Timely Results: The use of ML algorithms provides quick predictions, facilitating rapid decision-making and timely adjustments in network planning and optimization.

c. Cost-Effectiveness: The approach is computationally less expensive compared to traditional methods, reducing the overall cost of network performance monitoring and optimization.

d. Efficient Diagnosis: The ML models enable efficient detection of network issues, allowing for swift recommendations and resolutions. This leads to improved network performance and service quality.

3 Methodology

This research was conducted following the procedures outlined below.

3.1 Data Collection Process

The data collection process involved conducting drive tests around the University of Hull and nearby locations, including Hull City Centre, Barton Upon Humber, and Newland, which served as use cases. The primary tools used in this process were:

a. **Smartphones:** Redmi Note 7 (4G) and Samsung Galaxy A32 (5G) were used to record and store the logged data.
b. **SIM Cards:** SIM cards from four different Mobile Network Operators (MNOs)/Mobile Virtual Network Operators (MVNOs)—Three, EE, TESCO, and Vodafone—were utilized to ensure network availability during the measurements.
c. **G-NetTrack Pro Application:** This open-source application was employed to capture and log mobile network parameters during the drive tests.

The smartphones, equipped with an in-built Global Positioning System (GPS), were used to log data in real-time as the drive tests were conducted. Each benchmarking test lasted approximately one hour per location, except for Barton Upon Humber, where the test duration was slightly shorter due to its sparse population and fewer base transceiver stations (BTS) or nodes. The benchmarking process involved testing all four MNOs/MVNOs simultaneously, facilitated by the smartphones' capability to support two mobile networks each. This allowed for the collection of comprehensive data across different network operators in the same timeframe. Table 2 below provides more detailed information about the measurement locations and the duration of each test.

Table 2. Drive Test Measurement Locations and Test Duration of This Research

Drive Test Location	**Test Duration (Hr. Min)**
Around The University of Hull – Main Study	1.24
Barton Upon Humber – Use Case 3	0.13
Hull City Centre – Use Case 1	1.18
Newland – Use Case 2	1.02
Median Test Duration (Hr. Min)	1.10

3.2 Data Cleaning Process

The log files generated from the Drive-Tests were initially in text document (.txt) format and were subsequently converted into comma-separated value (.csv) format to facilitate further processing. The CSV data were then imported into Python using the Jupyter Notebook environment for detailed cleaning. During the cleaning process, missing values, outliers, duplicates, and unnecessary strings were systematically identified and removed. Outliers were detected and handled using a combination of techniques, including the Interquartile Range (IQR) method, Local Outlier Factor, and domain-specific knowledge. Figure 1 below illustrates the process of outlier detection and removal in the RSRP distribution across the mobile networks, where IQR and domain expertise were employed to ensure data accuracy and reliability.

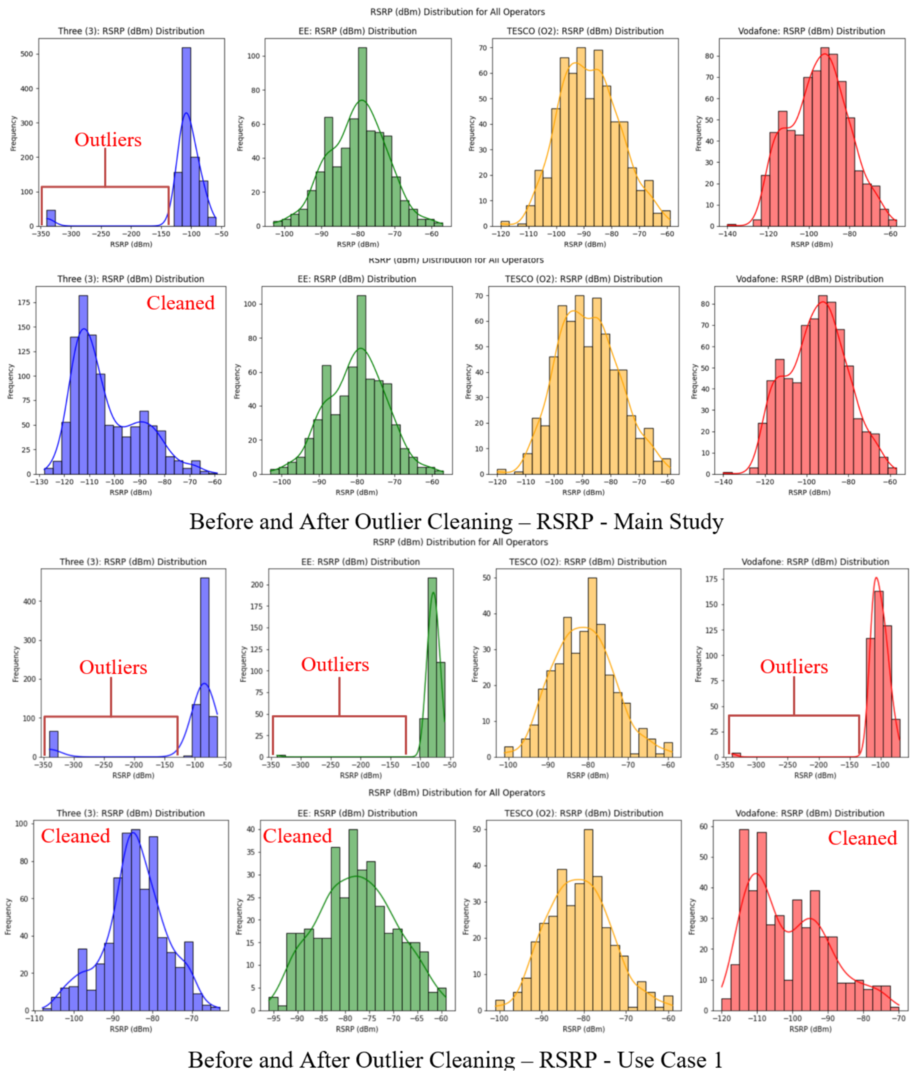


Fig. 1. RSRP distribution of all four MNOs/MVNOs showing potential outliers before and after cleaning with IQR and Domain Knowledge

3.3 Exploratory Data Analysis (EDA)

During the EDA phase, classes were created to facilitate classification predictions, mapping the RSRP values into categories of excellent, good, fair, and bad coverage, and the RSRQ values into categories of excellent, good, fair, and poor quality. Table 3 and Figure 2 provide further details on these classifications. Visualizations were then utilized to benchmark the RSRP and RSRQ values, allowing for the validation of changes made during the data cleaning process.

Table 3. Class Mapping (Legend) for Classification

Colour	Class Label	RSRP (dBm)	Colour	Class Label	RSRQ (dB)
Light Green	Excellent	>=-75	Blue	Excellent	>-8
Dark Green	Good	>=-95 - <-75	Dark Green	Good	>=-14 - <-8
Yellow	Fair	>=-105 - <-95	Yellow	Fair	>=-18 - <-14
Red	Bad	<-115	Red	Poor	<-18

3.4 Data Preprocessing

The data preprocessing phase began with the selection of the most relevant features or KPIs for building the regression and classification prediction models. This selection was guided by a correlation matrix, accompanied by a heatmap visualization, to represent the input features. The already labeled RSRP and RSRQ values were selected as the target outputs. To handle categorical variables, one-hot encoding was applied, converting these entries into binary values (1s and 0s). Following this, the dataset was split into training (80% of the sample) and testing (20% of the sample) subsets. To minimize model overfitting and ensure data balance, regularization was applied using Standard Scaler, marking the end of the preprocessing stage.

3.5 Machine Learning (ML) Modelling

The modelling process began with the development of a regression model aimed at predicting coverage (RSRP) and quality (RSRQ) using a variety of supervised ML algorithms. The base models employed included Decision Tree (DT), Extra Trees (ET), Extreme Gradient Boosting (XGB), Light Gradient Boosting Machine (LightGBM), Deep Neural Network (DNN), Multi-Layer Perceptron (MLP), Support Vector Regressor (SVR), K-Nearest Neighbour (KNN), Gradient Boosting (GB), and Random Forest (RF). An Ensemble Learning (EL) technique, specifically voting, was then applied to combine these base models, utilizing a 10-fold Cross-Validation (CV) to prevent overfitting. Following the regression modelling, a classification model was developed to similarly predict RSRP and RSRQ. The base models used for classification included Logistic Regression (LogisticR), MLP, DT, ET, Gaussian Naïve Bayes (GNB), LightGBM, Support Vector Machine (SVM), GB, KNN, and RF. This was also followed by EL modelling, applying stacking/voting methods, and a 10-fold CV. The EL model, combining the best-performing base models (RF, GB, ET, SVM, XGB, and

LightGBM for regression, and LogisticR, SVM, MLP, GB, ET, and RF for classification), achieved superior predictive performance. These algorithms were selected for their robustness, ease of use, computational efficiency, and strong research backing.

3.6 Model Evaluation

The effectiveness of the Regression models was assessed using key evaluation metrics including the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Coefficient of Determination (R^2). For the Classification models, evaluation was conducted using metrics such as Accuracy, Receiver Operating Characteristic Area Under the Curve (ROC_AUC), Precision, Recall, and F-1 Score, along with a classification and confusion matrix report to separate actual from predicted classes. Further discussion and analysis of these evaluation metrics and their implications for model evaluation are provided in the subsequent section.

4 Discussion

This section delves into the detailed analysis of the measurements and modelling results from the main study, along with a comprehensive examination of the outcomes from the use cases.

4.1 EDA and Feature Engineering

In this section, the results from the benchmark tests conducted across the four MNOs/MVNOs (Three, EE, TESCO, Vodafone) around the University of Hull and its surrounding areas are analyzed. Figure 2 showcases the distribution of coverage (RSRP) and quality (RSRQ) across various locations, categorized into areas of excellent, good, fair, bad, or poor performance. These categories were crucial for training the ML models to predict network performance effectively.

a. Exploratory Data Analysis (EDA)

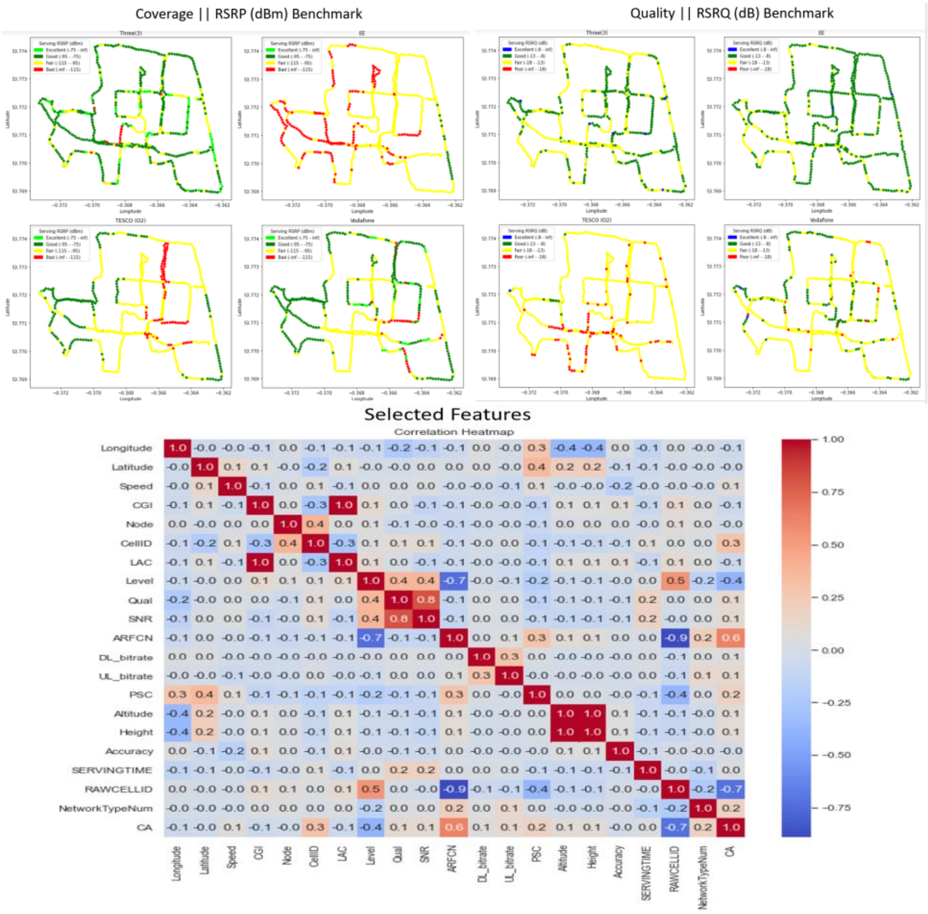
The exploratory data analysis focused on understanding the distribution of key variables and their relationships with the target metrics, RSRP (Level) and RSRQ (Quality). Visualizations were utilized to benchmark and validate the data post-cleaning, ensuring that the outlier removal and other preprocessing steps effectively prepared the data for model training. EDA also helped in identifying patterns in the data, such as geographic locations with consistently poor coverage, which could be indicative of underlying network issues.

b. Feature Engineering

Feature selection and engineering were pivotal in building accurate predictive models. Apart from the target variables (RSRP and RSRQ), several independent features were identified as significant contributors to the model's performance. These features included:

- *Longitude and Latitude*: Geographic coordinates were essential for spatial analysis of network performance.
- *Speed:* The speed of the device during the drive tests influenced signal quality, with faster speeds generally correlating with lower RSRP/RSRQ.
- *Cell Global Identity (CGI), Node, CellID, and Location Area Code (LAC):* These identifiers were crucial for distinguishing between different network cells and their performance characteristics.
- *Signal-to-Noise Ratio (SNR):* Higher SNR values generally indicated better signal quality, making this a key predictor for RSRQ.
- *Absolute Radio Frequency Channel Number (ARFCN):* This feature provides insight into the specific frequency bands used by the networks, which can affect coverage.
- *Downlink (DL) and Uplink (UL) Bitrate:* These features represented the data throughput in both directions, closely linked with the overall user experience and network quality.
- *Primary Scrambling Code (PSC) or Physical Cell Identity (PCI):* For 4G/5G networks, these identifiers were essential for understanding which cell or sector the device was connected to.
- *Altitude and Height:* These factors influenced signal propagation, especially in areas with varying topography.
- *Accuracy, Servingtime, and Rawcellid:* These additional parameters provided more context for the signal measurements, helping to refine the model's predictions.
- *Network Type Number and Carrier Aggregation (CA):* Network type (e.g., 4G, 5G) and the use of carrier aggregation were significant factors in determining RSRP and RSRQ.

The features were selected based on their correlation with the target variables, where strong positive or negative correlations (close to +1 or -1) indicated high feature importance. Additionally, domain knowledge played a crucial role in feature selection, ensuring that the models were built using variables that were not only statistically significant but also relevant in real-world network scenarios. The combination of these carefully selected features and the results from the EDA laid a strong foundation for building robust and accurate predictive models. These models were then used to identify and predict areas of varying network performance across the study area, providing valuable insights for network optimization.




```
Correlation Matrix of RSRP (Level)

Level            1.000000
RAWCELLID        0.545507
SNR              0.377307
Qual             0.368402
LAC              0.116489
CGI              0.116489
Node             0.057250
CellID           0.054892
SERVINGTIME      0.037228
Speed            0.019262
DL_bitrate      -0.007116
Latitude        -0.017828
Accuracy        -0.035629
UL_bitrate      -0.051221
Altitude        -0.055820
Height          -0.055820
Longitude       -0.074293
NetworkTypeNum  -0.157284
PSC             -0.195081
CA              -0.385331
ARFCN           -0.739975
Name: Level, dtype: float64
```

```
Correlation Matrix of RSRQ (Qual)

Qual             1.000000
SNR              0.810928
Level            0.368402
SERVINGTIME      0.188432
CA               0.113805
CellID           0.086341
NetworkTypeNum   0.032838
DL_bitrate       0.032079
Speed            0.031878
UL_bitrate       0.027811
LAC              0.002658
CGI              0.002658
RAWCELLID        0.001302
Latitude        -0.005305
Accuracy        -0.059183
Node            -0.060693
Altitude        -0.061697
Height          -0.061697
ARFCN           -0.099949
PSC             -0.140785
Longitude       -0.226743
Name: Qual, dtype: float64
```

Fig. 2. Coverage (RSRP) and Quality (RSRQ) Benchmark Plots, Feature Correlation Heatmap and Matrix Highlighting Their Relevance to The RSRP and RSRQ – Main Study

4.2 Regression Analysis - Main Study

For the coverage (RSRP) predictions, the MSE of most base models remained below 37.03, with exceptions in KNN at 50.86, MLP at 72.30, and DNN at 92.50. The RMSE for all base models was below 9.63, with MAE under 5.72, and MAPE below 6.3%. R^2 exceeded 71% for most models, except for MLP at 59.63% and DNN at 48.36%. Despite these variations, the overall coverage (RSRP) prediction performed very well, with the EL model (using a 10-fold CV) showing superior performance. The EL model achieved an RMSE of 3.87, MSE of 15.49, MAE of 2.69, MAPE of 2.75%, and an R^2 of 90.83%, indicating a high level of predictive accuracy. For the quality (RSRQ) predictions, the MSE of the base models stayed below 2.77, with RMSE under 1.67, MAE below 1.14, MAPE under 7.62%, and R^2 values above 62.74%, except for DNN at 54.49% and KNN at 45.85%, both of which were below 55%. The EL model (with 10-fold CV) also demonstrated strong performance in predicting RSRQ, with an MSE of 0.79, RMSE of 0.88, MAE of 0.6, MAPE of 4.28%, and R^2 of 81%. Figures 3 and 4 below provide further details.

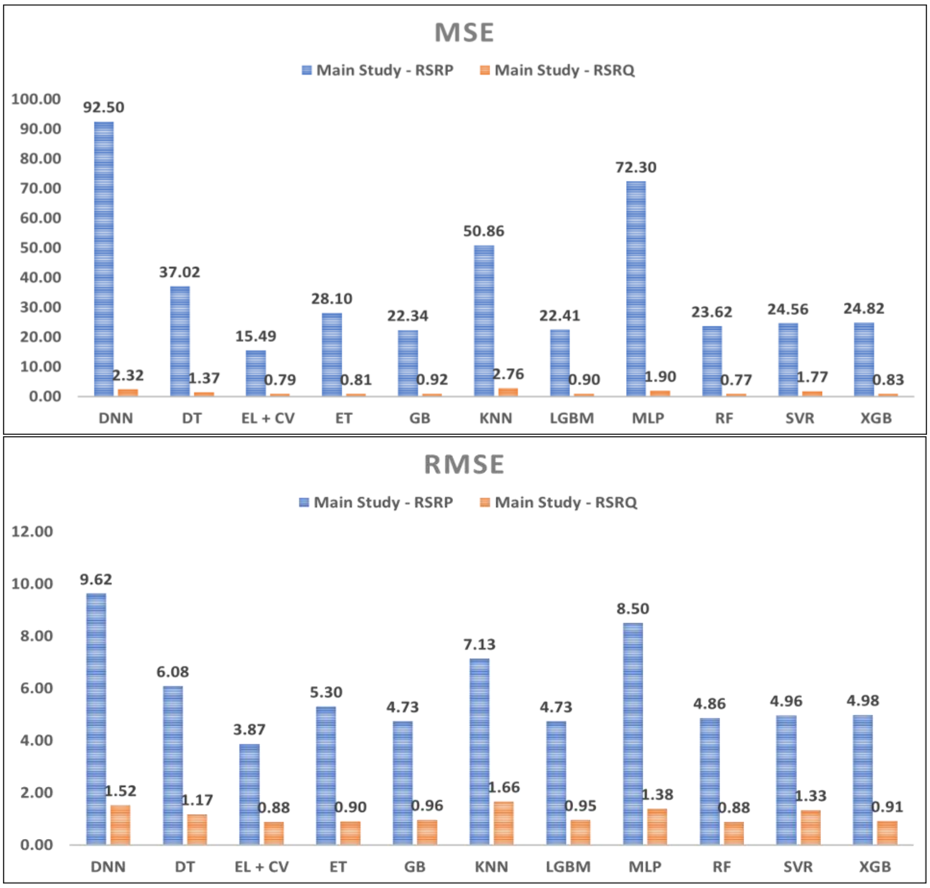


Fig. 3. MSE and RMSE Model Performance Evaluation for RSRP and RSRQ Predictions – Main Study

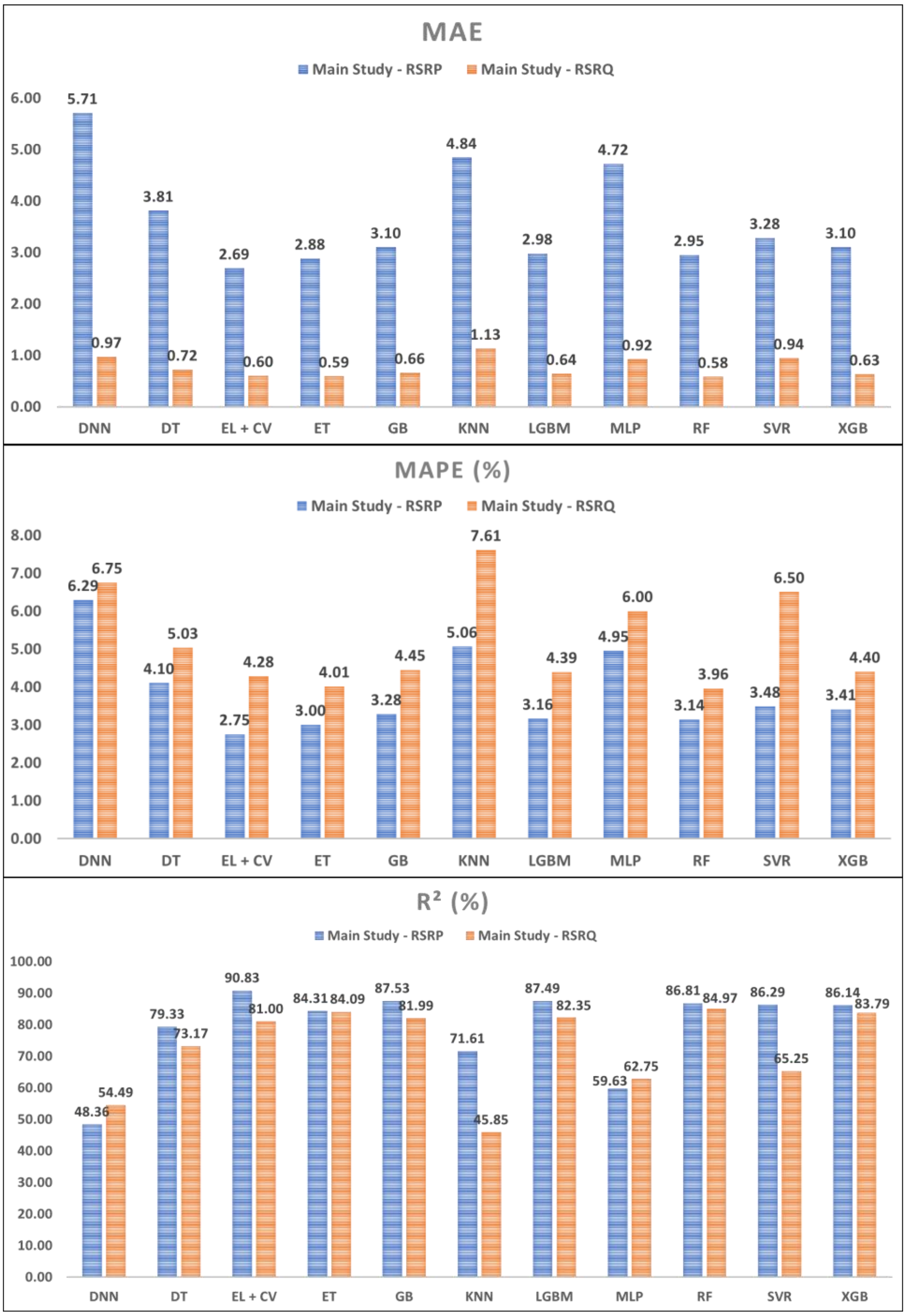


Fig. 4. MAE, MAPE, and R² Model Performance Evaluation for RSRP and RSRQ Predictions – Main Study

4.3 Classification Analysis - Main Study

For the coverage (RSRP) and quality (RSRQ) predictions, all base models achieved an accuracy greater than 70%, except for KNN, which recorded 66.99% for RSRP and 69.90% for RSRQ, and GNB, with 46.12% for RSRP and 63.59% for RSRQ. Additionally, the ROC_AUC values for all base models were above 75%, except GNB, which scored 69.69% for RSRQ. The EL model, incorporating a 10-fold CV, delivered strong overall performance, with an accuracy of 82% for RSRP and 85.51% for RSRQ. Figure 5 below provides further details, including the classification report and confusion matrix, which offer additional insights into the evaluation metrics and illustrate the separation between actual and predicted values.

Fig. 5. RSRP and RSRQ Model Performance Evaluation with Accuracy, ROC_AUC, Classification Report, and Confusion Matrix - Main Study

4.4 Use Case Analysis

Further coverage (RSRP) and quality (RSRQ) predictions were conducted in additional locations as use cases—Hull City Centre (case 1), Newland (case 2), and Barton Upon Humber (case 3)—to validate the effectiveness of the Regression and Classification models from the main study. These additional tests also demonstrated good performance across various metrics.

For RSRP and RSRQ predictions, the average RMSE for all base models and use cases was below 6. The R^2 values exceeded 61% for RSRP, except for the DNN model (24.04% in use case 2), DT (56.67% in use case 2), and MLP (52.42% in use case 2). For RSRQ, the R^2 values were above 50% across all base models and use cases, except for DT (38.89% in use case 3) and KNN (48.80%). The MSE remained under 36 for RSRP and below 4.08 for RSRQ across all models and use cases. The MAPE was less than 4.82 for RSRP and under 12.35 for RSRQ. Additionally, the MAE for all base models and use cases was below 4.25 for both RSRP and RSRQ. Accuracy was greater than 70% for both RSRP and RSRQ across all base models and use cases, except for GNB, which had accuracy below 51% for both RSRP and RSRQ in all three use cases. The ROC_AUC exceeded 67% for all models and use cases, except GNB, which had an ROC_AUC of 57.14% in use case 2. The Ensemble Learning (EL) model continued to perform very well, achieving R^2 values greater than 78.5% across all cases, MSE values below 13.4 for RSRP and below 2.4 for RSRQ, RMSE values under 3.66 for both RSRP and RSRQ, MAE values below 2.74 for both RSRP and RSRQ and MAPE values less than 3.3% for RSRP and below 9.65% for RSRQ. Figures 6, 7, 8, and 9 provide more detailed insights below.

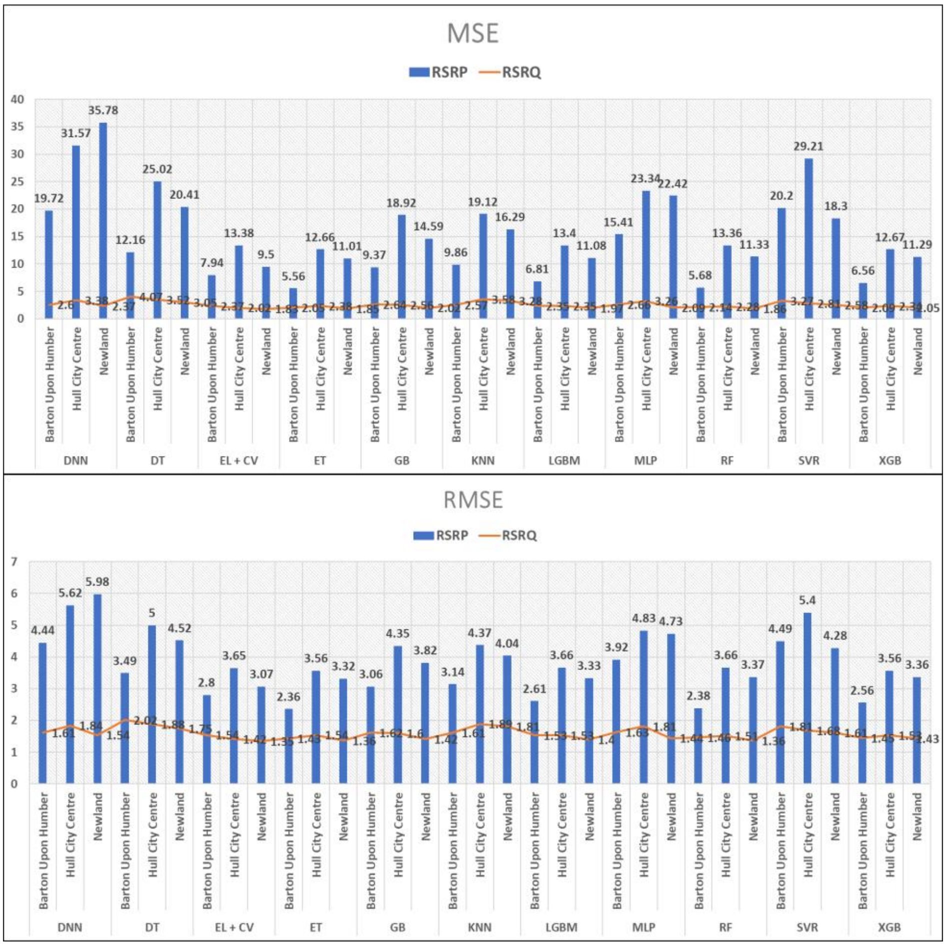


Fig. 6. MSE and RMSE Model Performance Evaluation for RSRP and RSRQ Predictions – Use Cases 1, 2, and 3

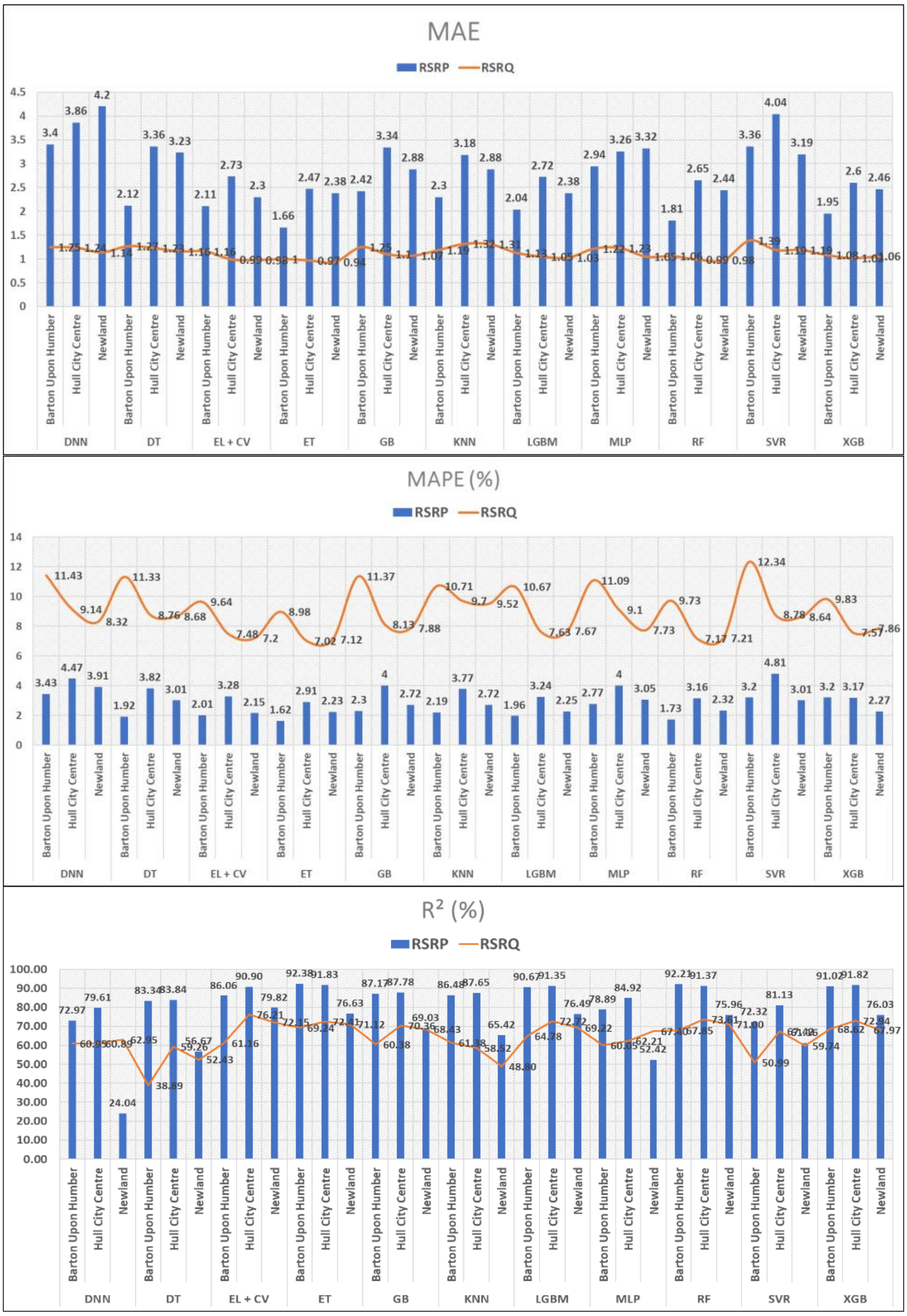


Fig. 7. MAE, MAPE, and R^2 Model Performance Evaluation for RSRP and RSRQ Predictions – Use Cases 1, 2, and 3

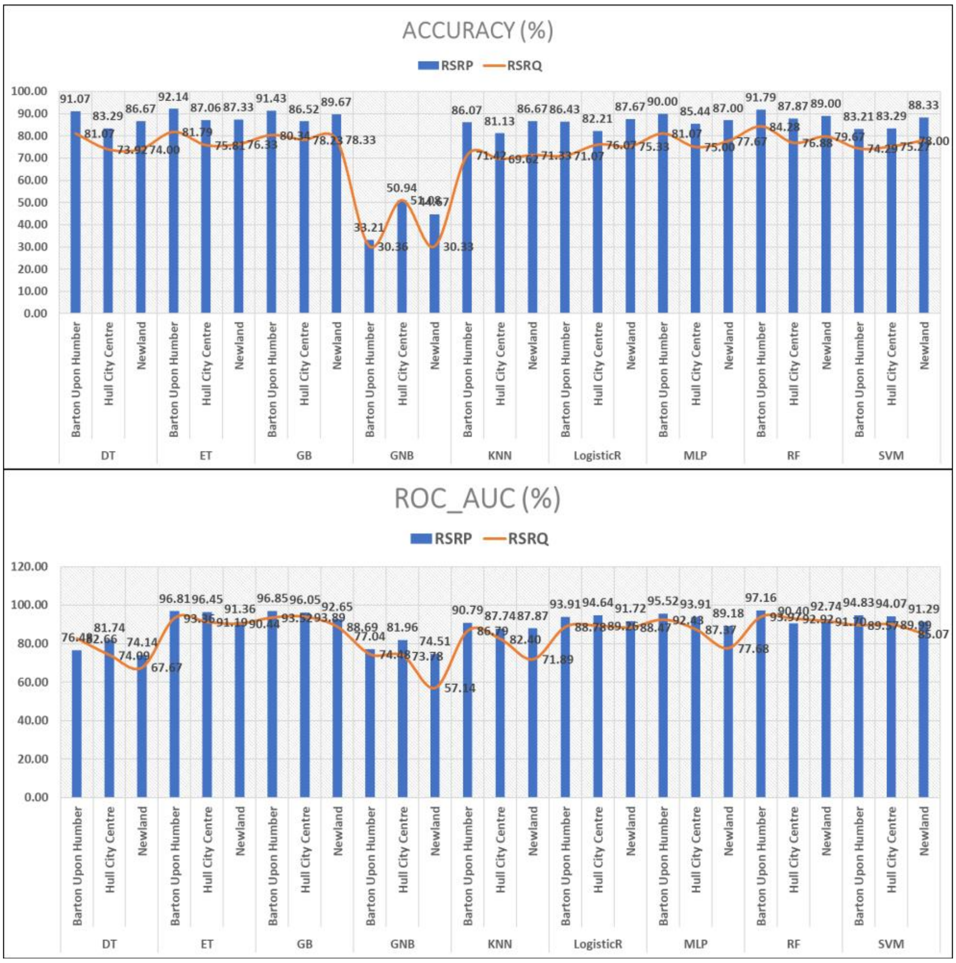


Fig. 8. Accuracy and ROC_AUC Model Performance Evaluation for RSRP and RSRQ Predictions – Use Cases 1, 2, and 3

Fig. 9. Classification Report and Confusion Matrix EL+CV Model Performance Evaluation for RSRP and RSRQ Predictions – Use Cases 1, 2, and 3

4.5 Summary

The overall model performance for this research, as shown in Figures 10, 11, and Table 4 below, demonstrates excellent results compared to related works [4, 5, 8, 9]. Notably, all errors (RMSE, MAE, MAPE for RSRP, and MSE for RSRQ) are below 4, except for MSE in RSRP (11.58) and MAPE in RSRQ (7.15%). The R^2 remains above 72% for RSRQ and over 86% for RSRP. Additionally, the ROC_AUC is above 85% for RSRQ and greater than 89% for RSRP, while Accuracy exceeds 81% for RSRQ and 87% for RSRP. These strong results are attributed to the high performance of base models such as RF, ET, LogisticR, GB, SVM/SVR, XGB, LightGBM, and MLP. A smart solution that MNOs/MVNOs can easily deploy to enhance QoS for end-users has been achieved [12].

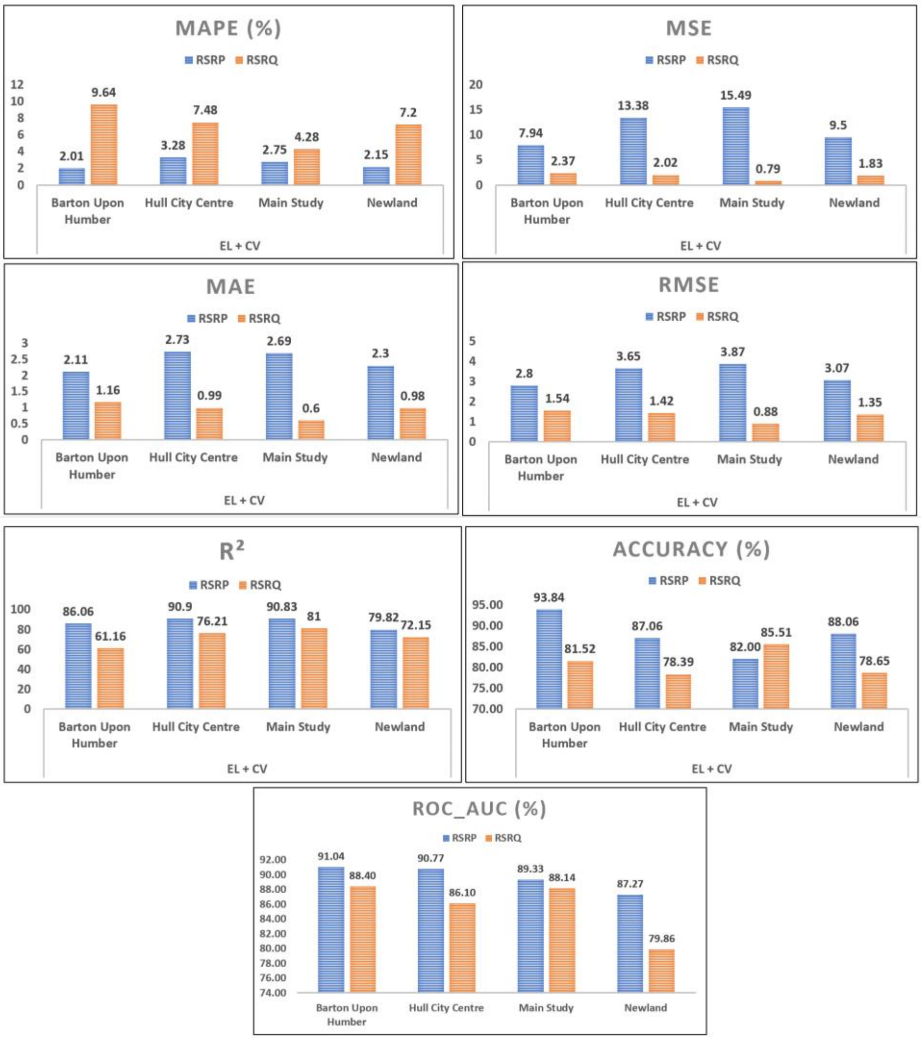


Fig. 10. MAE, MAPE, MSE, RMSE, R², ACCURACY, and ROC_AUC Model Performance Evaluation for RSRP and RSRQ Predictions Across All Locations

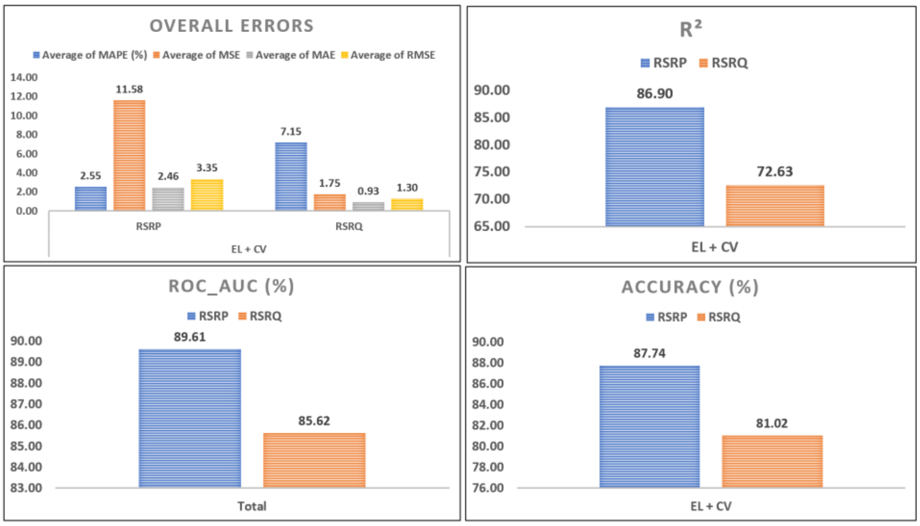


Fig. 11. Summarized Overall Model Performance for this Research with MAE, MAPE, MSE, RMSE, R^2, ACCURACY, and ROC_AUC

Table 4. Overall Model Performance Comparison with Related Work

Article Reference	KPI Prediction	Results (Related Work)	Results (This Research)	This Research Achievement
[9]	RSRP	<13 (GLM, MLP, DNN) and <2 (KNN) MAE	< **2.46** MAE	Lower MAE
[4]	RSRP	<7.45 RMSE, MAE, and MAPE, 63% R^2	<**4** RMSE, MAE, and MAPE, 72.63% R^2	Lower RMSE, MAE, MAPE, and higher R^2
[8]	RSRP	5.74 RMSE, 74% R^2	<**3.4** RMSE, **86.90%** R^2	Lower RMSE and higher R^2
[5]	RSRP	<7 RMSE for 4G LTE (T-Mobile and AT&T) >20 RMSE for WiMAX, Zigbee, and Industrial Network (at 5.8GHz)	<**3.4** RMSE	Lower RMSE

5 Conclusion

The application of multiple prediction techniques (Regression and Classification) and prediction KPIs (RSRP and RSRQ) using EL with the best-performing base models differentiates this research significantly from related works [4 - 11]. The overall average model performance—achieving metrics such as <4 RMSE and MAE, <7.16% MAPE, <11.59 MSE, >72% R^2, >85% ROC_AUC, and >81% Accuracy—demonstrates the effectiveness of using Ensemble Supervised Machine Learning algorithms to predict Mobile Network Coverage (RSRP) and Quality (RSRQ).

This research has successfully identified areas with excellent, good, and fair RSRP and RSRQ, which can be highly lucrative zones for MNOs and MVNOs. However, the study also identified coverage holes or areas with bad RSRP and poor RSRQ that require improvement. These issues could be addressed by MNOs/MVNOs through physical optimizations such as Antenna Tilt Change, Azimuth Re-Orientation, or Sector Swap Corrections, or through parametric adjustments [13, 14, 15] like Neighbour Relations Definition, Mobility Load Balancing (MLB) Tuning, and Random Physical Resource Block (PRB) Allocation Tuning.

This predictive AI solution is particularly valuable in scenarios where network data collection is limited or impossible, making it a potent tool for improving network quality, especially when traditional methods like drive testing are constrained.

6 Future Work

Future work could involve exploring the use of Live Network (or Radio Access Network – RAN) datasets obtained directly from MNOs/MVNOs, in combination with Drive-Test datasets, to enhance QoS and end-user experiences through improved ML modelling. Additionally, there could be a focus on how these ML models can be more effectively and efficiently deployed [16], offering practical insights into the seamless integration of these predictive tools into real-world telecommunications networks. This could pave the way for more dynamic and adaptive network optimization strategies, ultimately leading to better service delivery and customer satisfaction.

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