Study on the Performance of Machine Learning Models for Predicting Signal Strength in Cellular Networks

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ABSTRACT
The prediction of the signal strength of cellular networks has become a critical area of research with the deployment of 4G, LTE, and 5G technologies. Telecom operators can optimize the coverage areas, reduce call drops, and enhance user experience through accurate prediction of received signal strength. Complex environmental factors are ignored in traditional signal propagation models. Recently, various machine learning techniques have been applied to predict the signal strength of cellular networks, as their data-driven insights can adapt to dynamic network conditions. This paper explores several machine learning algorithms to build an optimal model that more accurately predicts the signal strength of cellular networks. The dataset used in the research was collected from Kaggle online dataset repository. It was divided into two partitions: a training set consisting of 80% of the data and a test set containing the remaining 20%. Then, different regression algorithms: K-Nearest Neighbors (KNN), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGB) were applied to the dataset. Finally, the RF and XGB models achieved the optimal performance i.e., the lowest MAE and RMSE values and the highest R^2 value. The knowledge extracted from these models can be used as a decision-making tool for telecom operators and organizations to accurately predict the signal strength of cellular networks in specific areas in the future.

Keywords
Machine Learning, Supervised Learning, Regression, Cellular Network, Signal Strength Prediction, Data Mining, Knowledge Discovery, Decision Making

1. INTRODUCTION
Traditional methods for network planning rely on empirical models, such as the Okumura-Hata model, the COST-231 model, and the ITU-R model [1-4]. Due to various environment factors, these models can be used for general signal strength predictions but they fail to capture real-time variations [5]. In reality, signal strength changes dynamically based on several factors, such as the distance from the nearest tower, obstacles (e.g., buildings, trees), weather conditions, and interference from other signals. Predicting signal strength can be useful in several real-life scenarios: tower placement and signal distribution for telecom companies, identification of weak network areas and improvement of network connectivity for customers, and enhancement of handover mechanisms in mobile networks for network engineers.

To ensure uninterrupted communication in modern wireless communication, the signal strength of cellular networks is considered a decisive factor, as it affects voice call quality, data transmission rates, and overall user experience [6]. Poor signal strength leads to dropped calls, slow internet speeds, and network congestion, negatively impacting both customers and service providers. The study by Tomic et al. [7] stated that the evolution of mobile networks towards 5G technology demands accurate signal strength prediction for several sectors, such as network optimization, capacity planning, and improving Quality of Service (QoS).

For large-scale cellular data analysis and network performance improvement, machine learning has emerged as a valuable tool. Nowadays, machine learning based models are implemented to uncover complex patterns from large-scale datasets and improve the accuracy of signal strength predictions. However, the non-linear nature of signal propagation is often not accounted for in traditional deterministic models, whereas machine learning based models can serve as a reliable alternative for predicting precise signal strength [8, 9].

The objectives of this research are as follows: to analyze the key factors those affect the signal strength of cellular networks; to implement several regression algorithms used in machine learning to predict signal strength; to compare different models based on their performance and accuracy; to use geo-spatial analysis to visualize and interpret the prediction results. The efficiency of cellular networks can be improved for network planning by achieving these objectives. Telecom operators and policymakers can utilize the findings of this study to design a decision-making model [17-19] that enhances the reliability and performance of cellular networks. In this paper, we have evaluated selected performance metrics: MAE, RMSE, and R^2 to validate the predicted signal strength obtained using various machine learning algorithms.

This paper is structured as follows: Section-2 describes previous related work on signal strength prediction using traditional models and machine learning techniques. Section-3 presents the dataset collection process, preprocessing steps and the application of machine learning algorithms. Section-4 discusses the findings of the developed models using various evaluation metrics for comparison. Finally, Section-5 concludes the research and outlines possible future work to improve signal strength prediction in cellular networks.

2. RELATED WORKS

In the early stages, signal strength in different terrains was predicted using empirical models. These models were developed based on empirical formulas derived from real-life observations. The most commonly used empirical models for traditional signal strength prediction were the Okumura-Hata model, the COST-231 Hata model, and the ITU-R model. The Okumura-Hata model was initially developed based on the measurements in Japan and was later extended for different frequency ranges [1]. It was mainly used to predict signal strength in areas near cities. Although it performed well in macro-cellular environments, it was not adaptable to real-time variations in signal conditions. The COST-231 Hata model, an extended version of Okumura-Hata model, covered frequencies ranging from 1500 MHz to 2000 MHz [2]. While it performed in satisfactorily for modern mobile communication, it provided limited accuracy in dense urban environments.

The ITU-R model was developed for radio propagation in both indoor and outdoor settings and was mainly used for radio network planning [3-4]. However, it faced generalization issues when applied to dynamic network conditions. These models were found to be reliable only under fixed assumptions and could not capture real-time environmental variations [10]. The accuracy of their prediction was reduced as they didn't consider interference, network congestion or device-specific variations. They also did not comply with new communication standards, such as 4G and 5G. Call quality, data transmission rates, and network coverage are mainly influenced by the signal strength of cellular networks. Typically, the signal strength is measured using metrics, such as Received Signal Strength Indicator (RSSI), Reference Signal Received Power (RSRP), and Signal to Noise Ratio (SNR) [11]. These metrics are useful for evaluating network quality, user experience and infrastructure performance.

However, the use of machine learning techniques has increased as they can learn from large datasets and provide better prediction results in terms of accuracy and adaptability. Several comparative studies have been conducted those evaluated the advantages of machine learning techniques for calculating signal strength. The investigation by Ali et al. [12] was conducted on real-world signal data using XGB, RF and DT algorithms. The most effective model was developed using the XGB algorithm which achieved the highest accuracy of around 92%. Afolabi et al. [13] implemented RF, SVM, and ANN algorithms to predict the signal strength of cellular networks. It was found that RF algorithm provided the best results in urban areas in terms of accuracy and computational efficiency.

The advantage of using RF in signal strength prediction is supported by many research studies. The study by Fauzi et al. [14] evaluated different machine learning models for Reference Signal Received Power (RSRP) prediction and found that the RF based ensemble tree model generated more accurate result. They recommended this approach for complex scenarios, such as multi-frequency and multi-environment settings. A hybrid model was proposed by Wang et al. [15] that combined Deep Learning techniques (LSTMs) with geo-spatial analysis. Their model outperformed conventional machine learning models in predicting signal variations over time. In the study by Chen et al. [16], Graph Neural Networks (GNNs) were introduced to estimate the network coverage. Their result demonstrated better performance than conventional machine learning models when applied to large-scale cellular network datasets.

These studies highlighted the use of ensemble learning algorithms (XGB, RF) and deep learning algorithms (LSTMs, GNNs) which achieved better results in the prediction of signal strength. However, some gaps have been identified in previous research studies, such as a lack of real-time adaptability, limited consideration of environment factors, the need for hybrid approaches in signal strength prediction, and challenges in 5G network prediction techniques.

3. PREDICTING SIGNAL STRENGTH IN CELLULAR NETWORKS

In this research work, a data-driven approach was followed to predict the signal strength of cellular networks using machine learning techniques. The dataset used for the development of different models was collected from the Kaggle online dataset repository [20]. The coding part was implemented on the Google Colab platform using Python. The output of the research can be analyzed for future use in decision-making purposes [17-19]. The workflow of the developed optimal model is described below.

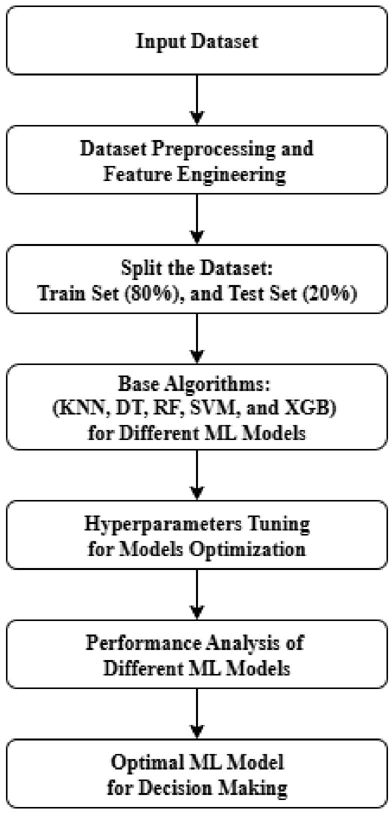

Figure 1: Steps for Predicting Signal Strength in Cellular Networks

3.1 Description of the Dataset

There were 16829 instances with 11 features and 1 label, i.e., target variable in the selected dataset [20]. A short description of the dataset features is given below.

Table 1: Description of the Dataset

Feature	Data Example	Data type
Timestamp	2023-05-05 12:50:40.000000 etc.	Categorical
Locality	Fraser Road, Gandhi Maidan etc.	Categorical
Latitude	25.599108619690096 etc.	Numerical
Longitude	85.1373547012626 etc.	Numerical
Signal Quality	0, 50, 80 in percentage	Numerical
Data Throughput	1.8638900372842315 etc. in Mbps	Numerical
Latency	129.1229140198042 etc. in	Numerical
Network Type	4G, LTE etc.	Categorical
BB60C Measurement	-95.81079071350962 etc. in dBm	Numerical
srsRAN Measurement	-105.45235850993319 etc. in dBm	Numerical
BladeRFxA9 Measurement	-99.92089156956251 etc. in dBm	Numerical
Target Variable: Signal Strength	-84.2741131853019 etc. in dBm	Numerical

3.2 Dataset Preprocessing and Features Engineering

The collected dataset [20] was preprocessed for different tasks, such as handling missing values, converting categorical features into numerical ones [21], features selection, and normalization [22]. Two features: Timestamp and Signal Quality were dropped from the dataset. Because, all instances were recorded at exact 10-minute intervals, and signal quality values were all zero due to a system error. Some categorical features, such as Network Type and Locality were converted into numerical features using a label encoder. Then, feature normalization was applied wherever necessary.

3.3 Split the Dataset

The preprocessed dataset was divided into two partitions: a train set consisting of 80% of the data and a test set containing the remaining 20%. Then, different regression algorithms were implemented to develop a machine learning model with the best performance.

3.4 Applied Machine Learning Algorithms

To develop an optimal model that predicts the signal strength of cellular networks based on the available features, five machine learning algorithms were selected for the regression purpose. Before applying these machine learning algorithms, hyperparameters were tuned to optimize the learning process, and reduce training time [23]. In this case, the HalvingGridSearchCV technique was implemented for its better performance over the GridSearchCV technique [24].

3.4.1 K-Nearest Neighbors (KNN)

It is a simple, instance based algorithm that is used for both classification and regression purposes. It determines the status of new data points based on the majority status of its surrounding k nearest neighbors status in the selected feature space [25].

3.4.2 Decision Tree (DT)

It is a supervised learning algorithm used for both classification and regression tasks. It recursively splits the data based on feature values and creates a tree based structure for decision making. In addition, it aims to partition the data into subsets with homogeneous target values [26].

3.4.3 Random Forest (RF)

It is an ensemble learning method that builds multiple decision trees during model training. Then, it generates a discrete output in the form of classes for classification or a continuous value for regression purposes. Predictive accuracy and overfitting can be improved using this approach [27].

3.4.4 Support Vector Machine (SVM)

It is a supervised learning algorithm that is used for classification and regression purposes. To separate the data points of different classes in the feature space, it finds the hyperplane and maximizes the margin between them [28].

3.4.5 Extreme Gradient Boosting (XGB)

It is an optimized version of the gradient boosting framework that is designed with speed and performance in mind. It allows the optimization of arbitrary differentiable loss functions and builds additive models in a forward, stage-wise manner [29].

4. RESULT ANALYSIS

In this paper, the dataset [20] used contains 16,829 instances with 11 features of cellular networks. It was analyzed to predict the signal strength of cellular networks using various regression algorithms: KNN, DT, SVM, RF, and XGB. These algorithms are mostly used in the development of machine learning models.

4.1 Performance Evaluation Metrics

The performance of the machine learning models was evaluated using three types of metrics to determine the optimal model for predicting the signal strength of cellular networks.

4.1.1 Mean Absolute Error (MAE)

It calculates the average absolute difference between the actual and predicted values. A lower MAE indicates that the predicted values are close to the actual values [30].

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Here, n = total number of signal instances,
y_i = actual value of the signal strength, and
$\hat{y}_i$ = predicted value of the signal strength

4.1.2 Root Mean Squared Error (RMSE)

It calculates the standard deviation of the estimated errors. A lower RMSE indicates betters results. A significantly higher RMSE compared to MAE suggests the possibility of large errors in some predictions [30].

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}}$$

Here, n = total number of signal instances,
y_i = actual value of the signal strength, and
$\hat{y}_i$ = predicted value of the signal strength

4.1.3 R-Squared (R^2)

It is indicates the capacity of the model to explain variance in the collected data. A higher R^2 value, i.e., close to 1, indicates the model can describe most of the variability in the target attribute [30].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

Here, n = total number of signal instances,

y_i = actual value of the signal strength,
$\hat{y}_i$ = predicted value of the signal strength, and
$\bar{y}_i$ = mean value of the signal strength

4.2 Performance Comparison

The performance of the developed machine learning models is presented in Table 2 using selected evaluation metrics for the signal strength prediction of cellular networks.

Table 2: Result Statistics of Different ML Models

ML Model	Train MAE	Test MAE	Train RMSE	Test RMSE	Train R^2	Test R^2
KNN	2.2158	2.4421	2.8089	3.0967	0.7314	0.6607
DT	1.3477	1.3705	1.8505	1.8533	0.8834	0.8785
RF	1.0326	1.1876	1.5932	1.7240	0.9136	0.8948
SVM	1.2272	1.2297	1.7609	1.7505	0.8944	0.8916
XGB	1.1482	1.1970	1.6906	1.7322	0.9027	0.8938

Firstly, the train MAE, RMSE, and R^2 values of the KNN model are: 2.2158, 2.8089, and 0.7314 and the test values of these metrics are: 2.4421, 3.0967, and 0.6607. The differences observed among these metrics for both the train and test sets are: 0.2263, 0.2878, and 0.0707 for the KNN model.

Secondly, the train MAE, RMSE, and R^2 values of the DT model are: 1.3477, 1.8505, and 0.8834 and the test values of these metrics are: 1.3705, 1.8533 and 0.8785. The differences observed among these metrics for both the train and test sets are: 0.0228, 0.0028, and 0.0049 for the DT model.

Thirdly, the train MAE, RMSE, and R^2 values of the RF model are: 1.0326, 1.5932, and 0.9136 and the test values of these metrics are: 1.1876, 1.7240, and 0.8948. The differences observed among these metrics for both the train and test sets are: 0.155, 0.1308, and 0.0188 for the RF model.

Additionally, the train MAE, RMSE, and R^2 values of the SVM model are: 1.2272, 1.7609, and 0.8944 and the test values of these metrics are: 1.2297, 1.7505, and 0.8916. The differences observed among these metrics for both the train and test sets are: 0.0025, 0.0104, and 0.0028 for the SVM model.

Lastly, the train MAE, RMSE, and R^2 values of the XGB model are: 1.1482, 1.6906, and 0.9027 and the test values of these metrics are: 1.1970, 1.7322 and 0.8938. The differences observed among these metrics for both the train and test sets are: 0.0488, 0.0416 and 0.0089 for the XGB model.

Generally, a smaller gap between the train and test metrics indicates that there was no overfitting. Overfitting and underfitting issues are resolved using hyperparameter tuning techniques [23]. As the difference found between both the train and test set metrics is negligible, all the developed models were trained perfectly. Moreover, MAE, RMSE and R^2 values are considered for the performance analysis of different regression models. The best performing models will have the lowest MAE and RMSE values, and the highest R^2 value.

According to the analysis of the result statistics and the concept of an optimal model, the RF and XGB models achieved the highest performance, while the SVM and DT models showed the second highest performance, with results close to the top-performing models. As the KNN algorithm is dependent on the distance metric, i.e., Euclidean distance formula, it is highly sensitive to irrelevant or noisy features [31]. Therefore, the KNN model provided the least accurate performance compared to the other developed models and there were significant fluctuations in the KNN model in all graphs.

Figures 2, 3, and, 4 visually represent the performance of different regression algorithms applied to the dataset [20], based on the statistics in Table 2.

The knowledge extracted by analyzing the best performing models can be used later for efficient decision-making [17- 19]. This can assist the researchers and telecom operators in predicting the signal strength of cellular networks more precisely.

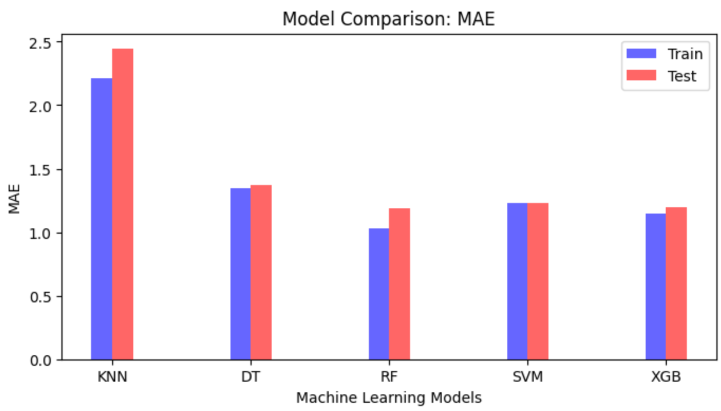

Figure 2: MAE Comparison Across Different ML Models

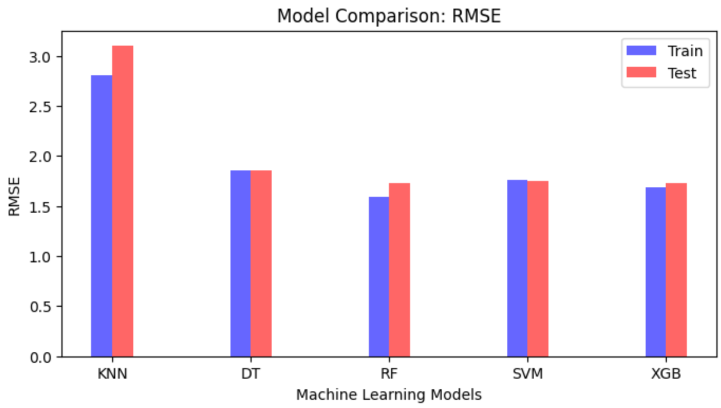

Figure 3: RMSE Comparison Across Different ML Models

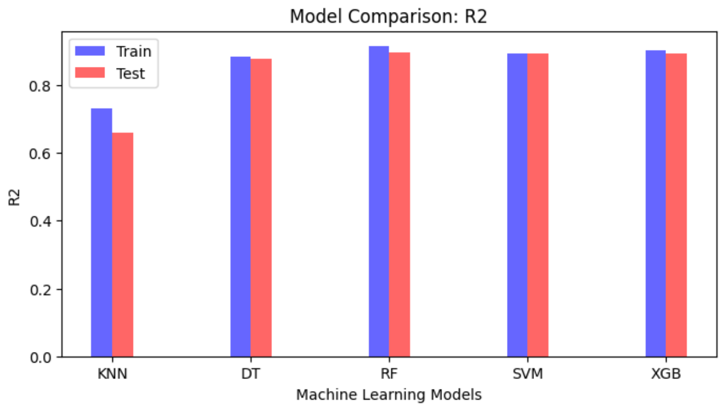

Figure 4: R^2 Comparison Across Different ML Models

5. CONCLUSION AND FUTURE WORK

This paper presents an optimized machine learning regression model for predicting cellular network signal strength. It used a dataset collected from the Kaggle online dataset repository. After data preprocessing and feature engineering steps, the dataset was divided into two partitions: a train set and a test set. Several regression algorithms: KNN, DT, SVM, RF, and XGB were applied to the dataset to train the desired machine learning models with hyperparameter tuning for optimal performance. The performance of the developed models was evaluated using selected regression metrics: MAE, RMSE, and R^2. The optimal performance i.e., the lowest MAE and RMSE values and the highest R^2 value were achieved by the RF and XGB models. Then, second highest performance was achieved by the DT and SVM models, while the KNN model generated the lowest performance.

This research explored various regression algorithms and analyzed the performance of different machine learning models. The performance of the optimal model can be further improved by expanding the dataset scope, integrating time-series data for temporal analysis, enhancing model performance with deep learning and federated learning techniques, adapting models for 5G and above networks, and deploying the optimal model as a web application or mobile application for future use as a reliable decision-making tool. The large-scale dataset can enhance the generalization of the model as there will be more instances related to cellular network signal strength. Additionally, the dataset should be updated regularly for the target areas. The integration of time-series data helps in analyzing seasonal and weather related variations in signal strength. Several deep learning techniques: ANN, CNN, and RNN can be explored for improved accuracy. Federated learning is another technique to train the models while preserving the user privacy. This dataset only included data of 3G, 4G, and LTE network but the addition of 5G or more advanced network related data could improve the performance of the models.

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