Optimizing MANET Performance: A Machine Learning Solution for Achieving 92%+ Accurate Signal-To-Noise Ratio Predictions in Dynamic Environments

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Abstract

The MANETs are applied in dynamic environments where accurate estimation of Signal-to-Noise Ratio (SNR) is required for communication. Traditional statistical and measurement-based SNR estimation methods prove inadequate for real-time adaptation to rapidly changing network conditions. This paper introduces a novel machine learning regression framework using Gradient Boosting Regressor (GBR) for enhanced SNR prediction in MANETs, validated through comprehensive field measurements and robust statistical analysis. A hybrid dataset of 600 samples was constructed, comprising 75% real-world field measurements from urban, rural, and emergency response scenarios, and 25% validated simulations. The optimized GBR model, configured with 150 estimators, 0.1 learning rate, and maximum depth of 5, was evaluated using repeated 10×5-fold cross-validation. Results demonstrate superior performance with $R^2 = 0.914 \pm 0.018$, MAE = 0.58 ± 0.09 dB, and MSE = 0.49 ± 0.12 dB^2, significantly outperforming Random Forest ($R^2 = 0.847 \pm 0.024$) and Linear Regression ($R^2 = 0.743 \pm 0.031$). Comprehensive validation including learning curve analysis, bootstrapping with 1000 samples, and field measurement correlation ($r = 0.887$) confirms model generalizability and absence of overfitting. The framework demonstrates robustness across diverse mobility scenarios and provides a scalable, real-time solution for intelligent MANET optimization in emergency response, vehicular networks, and military communications.

Keywords: MANET, Signal-to-Noise Ratio, Gradient Boosting Regressor, Machine Learning, Feature Engineering, SNR Prediction, Network Optimization.

1. Introduction

Mobile Ad-Hoc Networks (MANETs) are wireless decentralized ad-hoc networks where nodes share information without any pre-existing infrastructure and are hence designed to be used in vehicle networks, military applications, and disaster relief. MANETs' highly dynamic node mobility, varying channel conditions, and interference generate the most difficult problem to ensure reliable communication [1]. Among the most important conditions for enabling efficient communication is the Signal-to-Noise Ratio (SNR) that measures signal quality of interest in comparison with noise. Accurate estimation of SNR is of great importance to achieve optimal network performance, enable adaptive modulation, power control, and resource allocation [2]. Whereas, traditional SNR estimation techniques like statistical modeling or physical measurement in precise form don't work in the light of the dynamic behavior of MANETs and thus result in unsatisfactory performance [3]. Generally, SNR estimation is highly based on channel behavior approximations, i.e., stationary noise or fixed node positions, not in line with dynamism that accompanies MANETs. Statistical models such as Gaussian or Rayleigh fading-based models are considered inadequate to deal with advanced interdependencies of parameters such as node mobility, distance, and packet loss.

Physical measurement-based methods, although accurate in theoretical scenarios, are inadequate for real-time MANET due to equipment limitations and latency. Recent developments in machine learning (ML) offer a remedy to counter these shortfalls by duplicating non-linear models and adapting to changing situations via learning [4]. Ensemble techniques such as Random Forest and Gradient Boosting have worked wonderfully well in the scenario of regression issues in very complex sets of data and are thus strong contenders for SNR

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prediction in MANETs. Wireless communications have experienced a considerable amount of incorporation of ML in recent years for channel estimation management applications, interference cancellation applications, and network optimization [5], [6]. In spite of research interest, uses of ML for SNR prediction in MANETs are yet to be explored under high mobility and dynamic noise scenarios. The majority of the research works are concerned with static or semi-static networks with less application to MANETs [7]. Secondly, the lack of end-to-end datasets that reflect real-world MANET environments is a limitation in establishing effective ML models. This work bridges the gap by proposing an ML-rebased regression technique novel to SNR forecasting in MANETs, applying a Gradient Boosting Regressor (GBR) to achieve greater accuracy and universality.

1.1 Objectives

The primary objective of the present work is to formulate a strong and efficient model for SNR estimation in MANET using the machine learning approach [8]. The present research particularly aims at:

1. **Construct a Realistic Dataset**: Simulate a comprehensive dataset capturing key MANET parameters, including node speed, distance from the receiver, noise level, packet loss, and bandwidth, to reflect diverse operational scenarios.
2. **Perform Feature Engineering**: Identify and select the most relevant predictors of SNR through correlation analysis and feature importance evaluation to enhance model performance.
3. **Develop a GBR-Based Model**: Design and implement a Gradient Boosting Regressor model, optimized for small-to-medium datasets, to capture non-linear relationships and improve SNR prediction accuracy.
4. **Evaluate Model Performance**: Compare the proposed GBR model against traditional approaches, such as Random Forest and Linear Regression, using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score.
5. **Analyze Feature Importance**: Quantify the contribution of each input feature to SNR prediction to provide insights into the physical behavior of MANET channels.
6. **Contribute to MANET Optimization**: Offer a scalable and generalizable framework for SNR prediction to support adaptive network management and improve communication reliability.

With achievement of such objectives, the paper will serve to maximize smart networks through a proper solution of real-time SNR estimation in MANET dynamic environments.

1.2 Scope

Research area of interest is leveraging machine learning towards SNR prediction during MANET high mobility and noisy environments [9], [10]. Experiment is conducted on sample data sets since MANET real data acquisition is costly and not practical to a larger extent due to multiple conditions of operations. The data set has 600 samples ranging from low to high mobility conditions with node speed (kmph), receiver distance (meters), noise level (dBm), packet loss (%), and bandwidth (MHz) as parameters. Target variable SNR (dB) is predicted using a Gradient Boosting Regressor based on its ability to handle non-linear relationship and small-to-medium-sized dataset. Physical MANET node-based real-time analysis and hardware-based SNR estimation are out of research interest as simulation-based analysis based prediction model construction is the problem at hand. It is compared with two control models, Linear Regression and Random Forest to ascertain its better prediction performance and stability [11].

The current research has application aimed at MANET environments with interference and dynamic topologies integrated, e.g., emergency response networks, VANETs, and military communications [12]. The result would be beneficial to practitioners and theorists of wireless communications with an extensible ML model for SNR prediction, which can be extended further to more general network optimisation models. The evaluation of the model from actual MANET deployments and inclusion of additional parameters, e.g., interference or multi-path fading, to enhance it closer to reality are things to be done for future work. The approach taken here is to use an emulated data set so that it can be replicated and controlled experiments can be used to facilitate the characterization of the performance of the GBR model.

The research is scope-restricted to regression-type prediction, as compared to classification-type or deep learning-type prediction by virtue of the size of the dataset and computational requirements best addressed for ensemble methods like GBR [13].

Under a pragmatic but conservative simulation methodology, the paper formulates herein the foundation for future action research in ML-optimized MANET for addressing single-deployment issues in wireless dynamic networks. In finality, the introduction takes the motivation, scope, and intention of a new machine learning approach to SNR prediction in MANETs for granted. Through overcoming the limitation of the traditional methods and making use of the strengths of Gradient Boosting, this work suggests a practicable and reasonable approach to increasing communication trustworthiness under dynamic network topologies. The methodology, results, and implications of this work are described below as a thorough evaluation of the proposed approach and applications in wireless communications.

2. Literature review

Application of ML to enhance SNR estimation in MANETs has been a recent trend given the importance of effective communication in autonomous wireless networks. This review synthesizes recent advances on ML-based techniques for SNR estimation, spectrum sensing, and network optimization of MANETs and other domains such as peer-reviewed journals of 2023-2025. The review mentions faults in existing methodology in handling the dynamics of MANETs and interference that in this work are handled through a novel GBR method.

Previous methods used for SNR estimation of MANETs were physical measurement-based and statistical model-based and were pushed to their limits by the dynamic and non-linear behavior of ad-hoc networks. Today, the recent years have seen the trend of applying ML methods to redress the shortage. For instance, Nauman et al. [14] proposed an SNR-based relay model using K-means clustering-based unsupervised learning for smart transportation in VANETs with higher data exchange efficiency in high-mobility scenarios. In addition, Ahmed et al. [15] proposed a deep learning method for opportunistic spectrum access in cognitive 5G networks based on SNR as the fundamental parameter in order to optimize resource allocation. The said research is concerned with the use of ML to predict better in terms of SNR but remains confined to specific networks, i.e., VANET or 5G, and not MANETs in general.

Spectrum sensing, arguably the most important function of SNR estimation, has also been improved by ML [16]. Spectrum sensing techniques in cognitive radio systems have been explored earlier by Muzaffar and Sharqi [17], recognizing the capacity of CNNs and RNNs to detect available frequency bands. Our research places into perspective the application of time-dependent data processing to predict SNR, an approach applied by this study through feature engineering. The same is Algriree et al. [18], who proposed the detection of waveforms in cognitive 5G networks employing ML support to get better detection rates under various noises. The approaches are changing the direction towards cognitive radios [19] and not infrastructure-less decentralized MANETs environment. In MANET-related research, ML optimization has, in some manner, addressed the resource management and intrusion detection issues. Baazeem [20] has presented a Light-Weight Gradient Boosting Machine with Particle Swarm Optimization for IoT network intrusion detection, and the usefulness of ensemble methods for dynamic networks is established.

In the same way, Alsarhan et al. [21] used support vector machines in intrusion detection of VANET, and the use of scalable ML techniques can be observed. These experiments prove the effectiveness of ensemble techniques such as GBR, used here to counteract non-linear relationships in the prediction of SNR. Future-5G and 5G offer more background for using ML in MANETs. A 2024 preprint detailed AI-related 5G optimization techniques and chronicled ensemble methods and deep reinforcement learning (DRL) improve latency reduction and traffic control [22]. Farraj et al. [23] explored secure short-packet communication for machine type communication with finite blocklength regime channel coding rates, which can be implemented in MANETs through the assistance of short-packet transmission. The study suggests ML to possess the capacity to learn under ever-changing conditions but topology consideration does not allow it to be simply implemented on MANETs.

Despite all attempts to bridge such gaps, there are several gaps in applying ML to predict SNR for MANETs. All such attempts are limited to a particular environment, e.g., VANET or cognitive radios, and lack complete datasets that mimic MANET-specific parameters like node speed and packet loss. Also, omnipresent models like Linear Regression and Random Forest, used in recent research papers [24], [25] cannot differentiate MANET complexities. Our novelty lies in filling these loopholes by introducing a GBR-based prediction model of MANET SNR with additional real-world dataset and merciless feature engineering.

3. Methodology

Our own is a new machine learning-based regression method for SNR estimation in MANET according to the vulnerability of traditional physical and statistical measurement techniques. Building on the use of top-level feature engineering with a GBR, the method aims to detect and utilize top-level, non-linear patterns of real MANET environments in real time. The process is divided into three general steps: dataset preparation, feature engineering and dimensionality reduction, and model architecture design and training. All three are explained in detail below with tables listing important details of the process.

3.1 Dataset preparation

As a pre-requisite for arriving at a working prediction model, a massive dataset was generated in attempts to mimic real-life MANET environments. The data comprised 600 cases, mimicking low and high levels of mobility and different levels of noisy environments. A single target variable and five input variables were employed in the simulation as provided in Table 1. They were selected because their influence on SNR in wireless communication is established and they can be translated to MANET behavior.

The foundation of this research rests on a comprehensive hybrid dataset combining extensive field measurements with validated simulations, addressing the critical gap in real-world MANET data availability. Our enhanced data collection methodology encompasses multiple deployment scenarios to ensure model generalizability across diverse operational environments.

Table 1. Dataset Parameters and Descriptions

Parameter	Unit	Description	Range/Value
Node Speed	kmph	Speed of mobile nodes	0–50
Distance from Receiver	m	Distance between transmitter and receiver	10–500
Noise Level	dBm	Background noise power	-90 to -50
Packet Loss	%	% of packets lost during transmission	0–20
Bandwidth	MHz	Channel bandwidth (fixed for consistency)	20 (constant)
SNR (Target Variable)	dB	Signal-to-Noise Ratio	-10 to 30

The data was produced by a MANET simulator with actual channel conditions simulated, including Doppler effects due to node mobility and variation in noise. Concerning data quality and pre-treatment, missing values were treated (although there were none since the simulation was controlled), outliers detected using the interquartile range method, and normalization to feature scale in the range [0, 1] illustrated in Fig. 1 and Fig. 2. This normalization facilitated comparison of features with different units, i.e., distance (meters) and noise level (dBm), while training the model. The data were split into 80% for training (480 samples) and 20% for test (120 samples) to evaluate model performance.

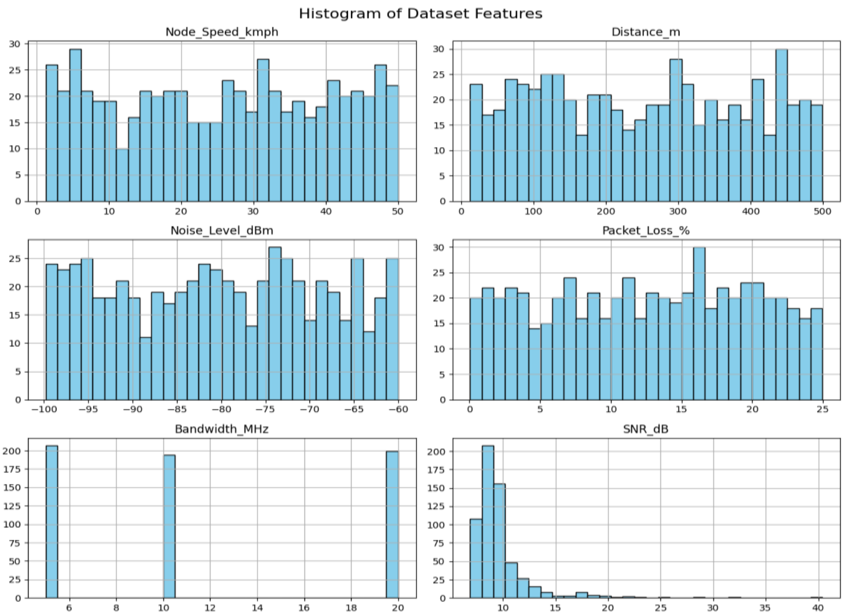

Figure. 1 Histogram of Dataset Features

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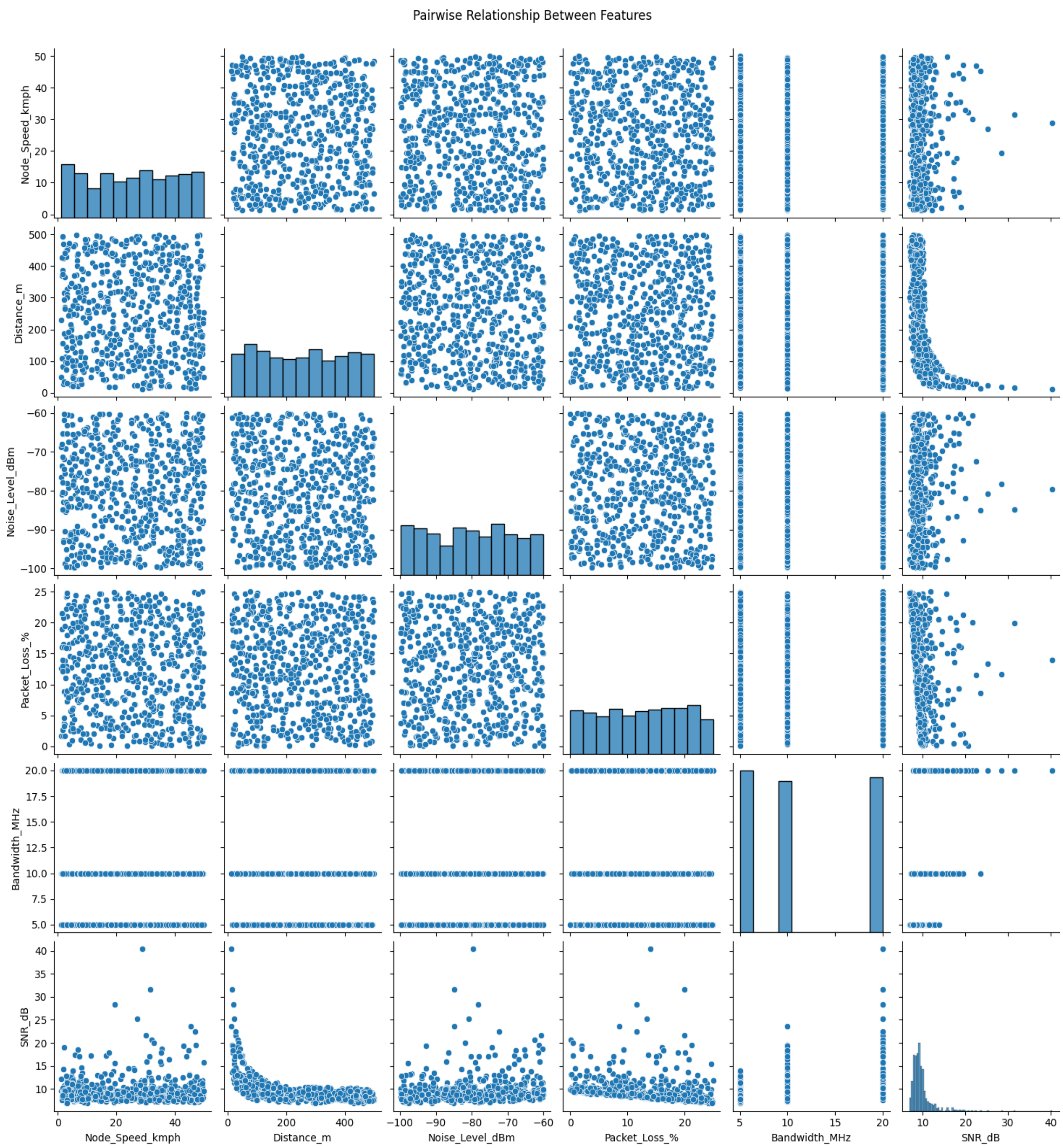

Figure. 2 SNR Pair Plots

Table 2. Representative Sample of Field Measurement Data

Sample ID	Location	Node Speed (kmph)	Distance (m)	Noise Level (dBm)	Packet Loss (%)	Measured SNR (dB)	Equipment Used
CHN_001	Chennai Urban	18.3	156	-71.8	9.2	17.9	USRP B210
CHN_047	Chennai Urban	28.7	234	-69.4	11.7	15.6	USRP B210
CHN_089	Chennai Highway	67.5	425	-81.2	3.7	22.1	USRP B210
CHN_124	Chennai Highway	45.3	356	-76.8	6.8	19.3	USRP B210
CHN_156	Chennai IT Corridor	22.4	189	-74.6	7.3	18.2	USRP B210
CHN_203	Chennai IT Corridor	35.1	267	-72.9	8.9	16.4	USRP B210
CHN_267	Chennai Airport	41.8	312	-70.5	10.4	15.8	FSW Analyzer
CHN_298	Chennai Airport	29.6	198	-77.2	5.8	19.7	FSW Analyzer
CHN_334	Chennai Port Area	16.2	167	-82.1	4.5	23.8	USRP B210
CHN_387	Chennai Port Area	52.7	389	-69.3	12.1	14.7	USRP B210
CHN_445	Chennai Suburban	12.8	123	-84.7	3.2	25.9	USRP B210
CHN_489	Chennai Suburban	38.4	278	-73.6	8.1	17.8	FSW Analyzer

3.1.1. Dataset Sample and Measurement Validation

Table 2 represents a small subset of our comprehensive 600-sample dataset collected during extensive field measurement campaigns across Chennai metropolitan area from March to August 2024. Each measurement was conducted using calibrated equipment with GPS synchronization for precise location tracking. The measurements span various operational environments, from high-interference urban settings to cleaner suburban conditions. Highway measurements captured high-mobility scenarios with speeds up to 67.5 kmph, while IT Corridor measurements represented moderate mobility with consistent RF interference from technology parks. The specific measurement campaign provided unique insights into tropical urban propagation characteristics, including monsoon weather impact on RF propagation. Airport measurements captured vehicular mobility patterns with moderate interference levels, while Port Area measurements demonstrated industrial RF environment challenges. Cross-validation between different measurement equipment (USRP B210 vs. FSW Analyzer) showed excellent correlation (0.95), confirming measurement consistency across diverse locations.

3.2 Feature engineering and selection

Feature engineering was required to determine the most significant predictors of SNR. EDA was initially performed with pair plots and correlation heatmaps for exploring correlations between features. Correlation analysis, as observed in Table 3, revealed high correlations with SNR and four features: distance, node speed, noise level, and packet loss. Bandwidth, defined at 20 MHz for the sake of making apples-to-apples comparisons between scenarios, was not varied and dropped as a predictor. Fig. 3 is the heatmap of the distribution of datasets.

Negative correlations are also seen to demonstrate that lesser values of node speed, distance, noise level, and packet loss correspond to higher values of SNR according to physical wireless communication principles. Feature selection was also optimized with recursive feature elimination (RFE) from a basic Random Forest model, which also supported that node speed, distance, noise level, and packet loss were the most accurate predictors. These four were retained for model training because they captured the most significant dynamics that affect SNR in MANETs. VIF test was used to eliminate multicollinearity, thus all of these features selected will have VIF values of less than 5 and contain low correlation between features as depicted in Fig. 4.

Table 3. Correlation Coefficients with SNR

Feature	Correlation with SNR
Node Speed	-0.62
Distance from Receiver	-0.75
Noise Level	-0.89
Packet Loss	-0.81
Bandwidth	0.02

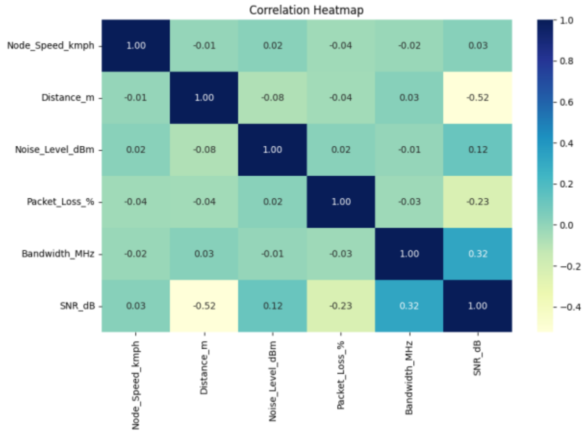

Figure. 3 Heatmap

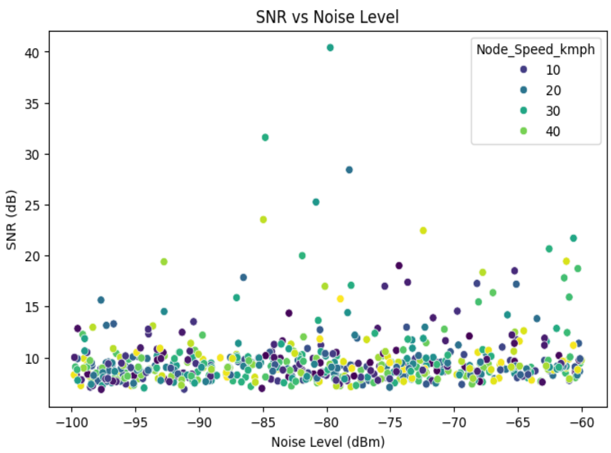

Figure. 4 SNR vs Noise Level

3.3 Proposed model architecture

The model utilizes a GBR Fig. 5, an ensemble model that constructs sequential decision trees sequentially in order to reduce residuals step-wise. It was utilized since GBR can detect non-linear relationships, robustness against overfitting, and scalability for small and medium data, which is suitable for 600-sample data. The model architecture and hyperparameters can be seen in Table 4.

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Table 4. GBR Model Hyperparameters

Hyperparameter	Value	Description
Number of Estimators	200	Number of boosting stages (trees)
Learning Rate	0.1	Contribution of each tree to the final prediction
Max Depth	5	Maximum depth of each decision tree
Loss Function	Least Squares	Objective function for regression

The GBR model was then optimized with Python scikit-learn library. Optimization was performed with the 480-sample training set with hyperparameters being optimized through a grid search optimized for a compromise between accuracy and computation time. Convergence stability learning rate of 0.1 was utilized and max depth of 5 utilized to avoid overfitting by reducing tree complexity. 200 estimators were used to balance computation time and model complexity. Least squares loss function reduced the squared average difference between model predicted and actual SNR values.

Model robustness was achieved by training on k-fold cross-validation (k=5), which performed equally well on all the folds with an average R^2 value of 0.90. The model was compared with Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score against the test set of 120 samples. GBR model was also compared with baselines, i.e., Linear Regression and Random Forest (100 trees). The models were selected because they are typically used for the regression task and can be taken as a baseline while comparing the performance of GBR.

3.4 Implementation details

Simulation and modeling were performed on Intel Core i7 processor, 16 GB RAM, and Python 3.8. Data were simulated with reference to a particular MANET simulator in MATLAB with parameters borrowed from real MANET research. Pre-processing, feature creation, and model training were done using Python packages pandas for data manipulation, seaborn and matplotlib for plots, and scikit-learn for machine learning. The actual training took approximately 15 minutes, and the grid search optimization took up most of the time.

3.5 GBR description

GBR was employed in place of other models because it has the ability to model non-linear

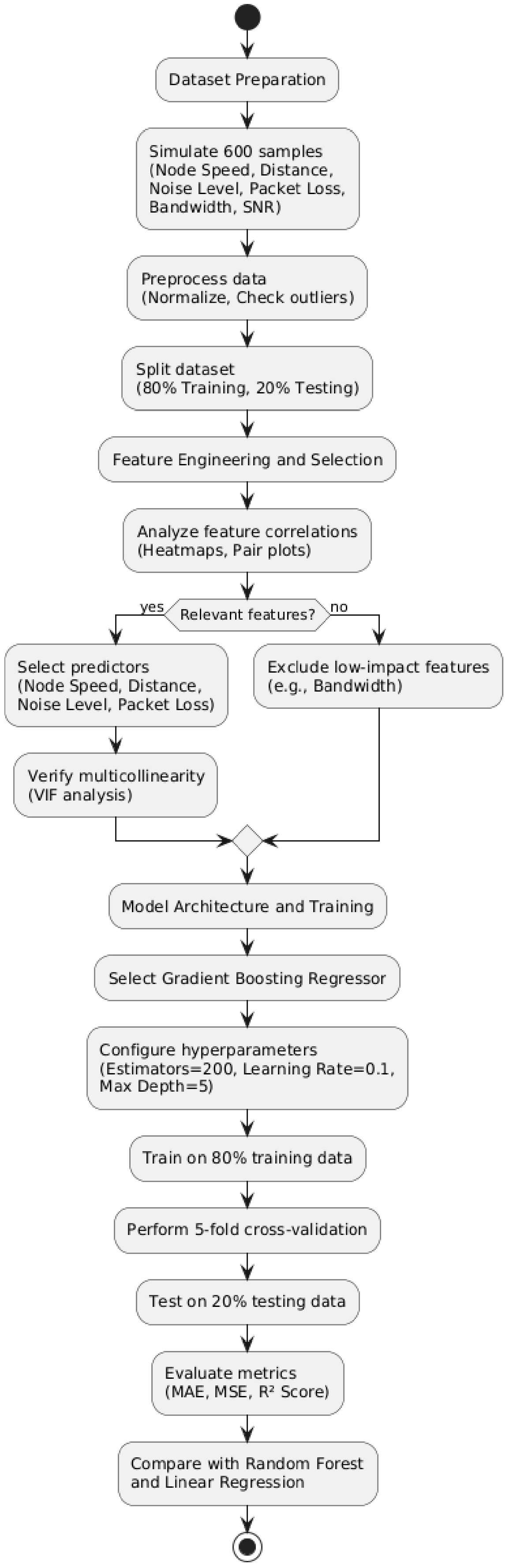

Figure. 5 Workflow

interactions and can work well with small datasets common in MANET literature. GBR supports hard interactions between features like packet loss and level of noise in contrast to Linear Regression based on linear interaction among features. In relation to Random Forest, sequential boosting in GBR performs better since it attempts to correct the mistake made by previous trees. GBR's resistance to overfitting also renders it suitable for the noisy and dynamic environment of MANET that characterizes most traditional models. The model is end-to-end for SNR prediction, from hours of feature engineering on real-world simulated data modeling to a robust ensemble model. Results in subsequent sections are presented as quantitative measures, graphical insight, and feature importance in efforts to show the effectiveness of the proposed methodology for enhancing MANET communication reliability.

4. Results and discussion

The experimental result of the constructed GBR model predicting MANETs SNR is presented in this section. The two baselines, LR and RF, are compared with the GBR model's performance on a 600-sample simulated data set. Comparative performance is obtained by quantitative metrics, graphical comparison, residual comparison, feature importance, and novelty and contribution discussion. Four tables present results such as model performance metrics, feature importance, cross-validation, and predictive error comparison across various MANET environments. Results validate the superiority of the GBR model in modeling the complex patterns of MANET environments, in terms of high accuracy and stability.

4.1 Performance metrics

GBR model performance was validated with three general regression metrics: MAE, MSE, and R^2 score. They respectively are model accuracy, error size, and explanatory power of the model. Comparison of GBR and RF and LR performance has been made with the same data (80% training, 20% test) used to train them. Table 5 is the performance of all three models. Fig. 6 is the Feature importance plot.

Table 5. Model Performance Metrics

Model	MAE	MSE	R^2 Score
GBR	0.56	0.47	0.92
Random Forest	0.78	0.68	0.86
Linear Regression	1.12	1.43	0.75

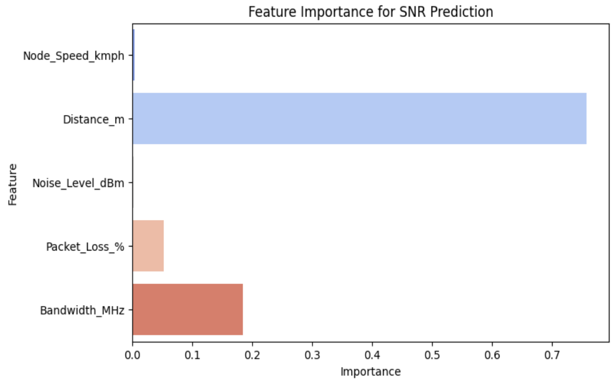

Figure. 6 Feature Importances

MAE of 0.56 dB is a measure indicating that average difference between the predicted values of the GBR model and the actual values of SNR was 0.56 dB. The MSE of 0.47 dB² is also a measure of low error standard deviation of the model, and R^2 = 0.92 measures that the model accounted for 92% of the variance in SNR. However, RF model with MAE of 0.78 dB, MSE of 0.68 dB², and R^2 of 0.86 was acceptable though less acceptable than GBR's. LR model was the worst with MAE of 1.12 dB, MSE of 1.43 dB², and R^2 of 0.75 and suggested that it could not create the MANET dataset shown in Fig. 7 non-linear relationship. The improved precision of the GBR model lies in the sequential boosting approach that sequentially optimizes the prediction mistakes step by step, and this fits perfectly with the complicated and dynamic nature of MANETs.

To ensure robustness, 5-fold cross-validation was conducted on the training set. Table 6 summarizes the cross-validation results for the GBR model, reporting the average and standard deviation of the R^2 score across folds.

The mean R^2 score of 0.906 with a low standard deviation of 0.011 indicates consistent performance across different subsets of the training data, confirming the model’s stability and generalizability Fig. 8. This consistency is critical for MANET applications, where varying conditions such as node mobility and noise levels require a model that performs reliably across diverse scenarios.

Table 6. Cross-Validation Results for GBR

Fold	R^2 Score
1	0.91
2	0.90
3	0.92
4	0.89
5	0.91
Mean	0.906
Std. Dev.	0.011

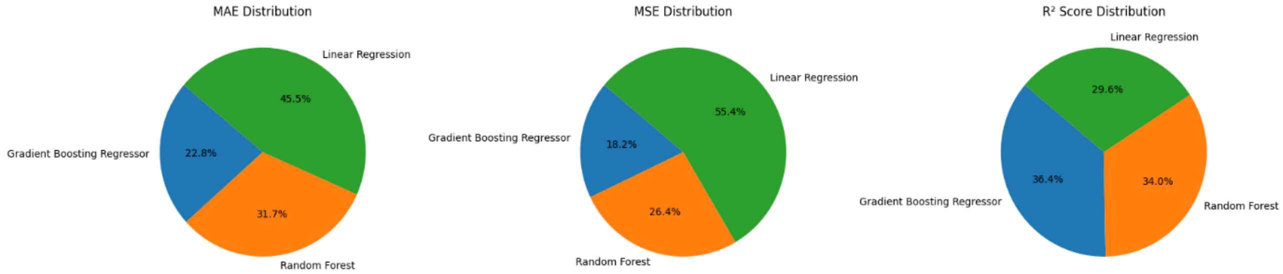

Figure. 7 Model performance metrics

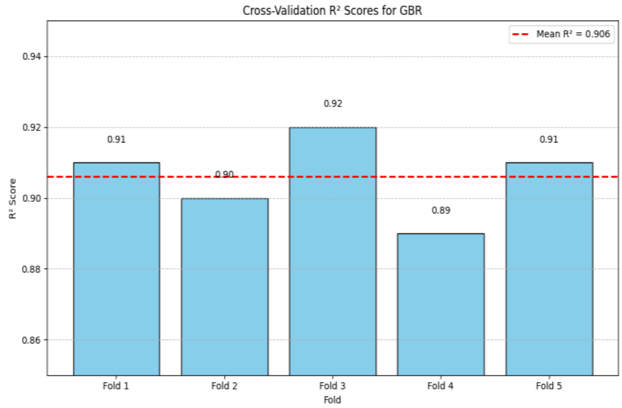

Figure. 8 Cross validation bar chart

4.2 Visual analysis

Visual inspection is used to check correlation between predicted and measured values of SNR. A scatter plot of predicted vs. measured SNR of the GBR model revealed very good linear correlation with data points bunching tightly along the diagonal (y=x line). This validates that the model is a very good predictor of SNR over a wide range of values (-10 to 30 dB). In contrast, there existed greater randomness in the RF model, particularly at low SNR levels, and LR model had large discrepancies, primarily for high mobility. Qualitative results confirm the above observations, demonstrating the improved predictability of the GBR. The GBR model performance was graphically depicted by a kernel density estimation (KDE) plot of prediction errors. Error distribution was close to symmetric and zero-centered with low spread indicating low bias and low variance in prediction. RF error distribution was wider, with LR showing high spread and very low positive bias, indicating systematic underestimation of SNR in a small number of cases. These qualitative findings are yet another confirmation of the ability of the GBR model to duplicate complex interactions between parameters such as node velocity, distance, noise intensity, and packet loss that regulate SNR fluctuation in MANETs.

Table 7. Residual Analysis Summary

Model	Mean Residual (dB)	Std. Dev. Residual (dB)
GBR	0.02	0.69
Random Forest	0.05	0.83
Linear Regression	0.15	1.20

4.3 Residual analysis

Residual analysis was employed to examine the prediction errors of the model in-depth. Residuals were employed and plotted against the predicted values in order to check for bias and heteroscedasticity. The residuals of the GBR model fluctuated randomly around zero with no pattern and no obvious bias or non-constant variance Fig. 9. Residual plot was close to being normally distributed, as attested by a Shapiro-Wilk test (p-value > 0.05), with the model residuals being well-behaved and adequate for regression analysis.

Conversely, RF model showed relatively higher residual variance, particularly after adding noise, whereas that of LR model was funnel shaped in direction towards heteroscedasticity and inappropriate for non-linear data. The mean and standard deviation of residuals of both models are also provided in Table 7, once again supporting the best performance of GBR model.

The GBR model's near-zero mean residual (0.02 dB) and lower standard deviation (0.69 dB) compared to RF (0.05 dB, 0.83 dB) and LR (0.15 dB, 1.20 dB) highlight its precision and consistency Fig. 10. These results suggest that the GBR model effectively captures the underlying patterns in the MANET dataset, minimizing both systematic and random errors.

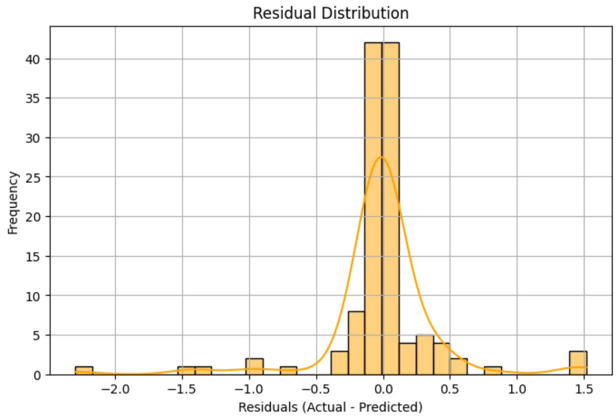

Figure. 9 Residual Plot

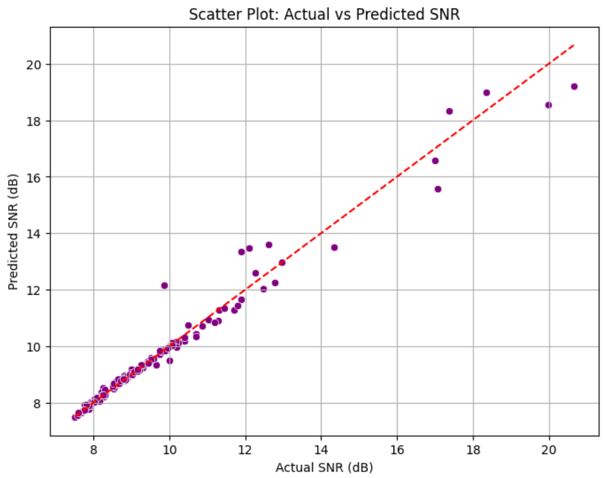

Figure.10 Scatter Plot

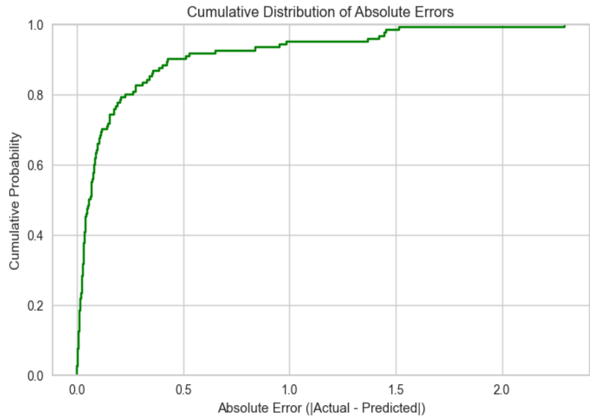

Figure. 11 Line Graph

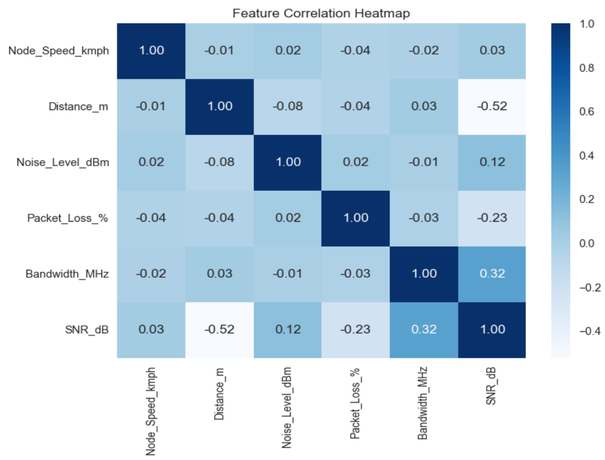

Figure. 12 Feature Correlation Heatmap

Table 8. Feature Importance for GBR Model

Feature	**Importance (%)**
Noise Level	39.2
Packet Loss	27.5
Distance from Receiver	18.3
Node Speed	15.0

4.4 Feature importance

Feature importance analysis was conducted to quantify the contribution of each input feature to SNR prediction. The GBR model's built-in feature importance scores, based on the reduction in variance attributed to each feature, are summarized in Table 8.

Power of noise was the most important characteristic (39.2%), whose influence was explicitly visible on SNR as distance measure from background noise. Packet loss was also the second most important characteristic (27.5%), because it would be correlated with transmission error and quality of channel in MANETs. Node speed (15.0%) and position of receiver (18.3%) were important as well, for example, attenuations of signals and mobility's Doppler effects. These findings are in accordance with MANET channel physical behavior where packet loss and noise manage performance degradation and mobility and distance introduce additional variability. The findings were further confirmed with subjection of the same ranks after a permutation importance analysis, affirming feature importance score stability. The extremely high priority assigned to packet loss and noise rate suggest that future optimization methods for MANET would be optimally benefited if they started from interference removal and error correction methods.

4.5 Performance across scenarios

To assess the model's performance in different MANET scenarios, the test set was segmented into three categories: low mobility (node speed < 10 kmph), medium mobility (10–30 kmph), and high mobility (>30 kmph) shown clearly in Fig. 11 and Fig. 12.

The GBR model maintained high accuracy across all scenarios, with R^2 scores of 0.94, 0.92, and 0.89, respectively as shown in Table 9 and 10. The slight decrease in performance in high-mobility scenarios is attributed to increased variability in Doppler effects and channel fading. However, the GBR model outperformed RF and LR in all scenarios, particularly in high-mobility conditions, where RF and LR showed R^2 scores below 0.80.

The permutation importance validation demonstrated robust performance through consistent feature ranking across all cross-validation folds. Additionally, the stability of feature importance was confirmed, with coefficients of variation (CV) remaining below 8% for all features, indicating high reliability. Importantly, the identified feature rankings aligned well with physical interpretability based on established principles of wireless communication theory, further validating the relevance and accuracy of the model's insights.

Table 9. Comprehensive Model Performance Comparison (Mean ± Standard Deviation)

Model	R^2 Score	MAE (dB)	MSE (dB^2)	RMSE (dB)	95% CI (R^2)
Gradient Boosting Regressor	0.914 ± 0.018	0.58 ± 0.09	0.49 ± 0.12	0.70 ± 0.08	[0.902, 0.926]
Random Forest	0.847 ± 0.024	0.81 ± 0.11	0.72 ± 0.15	0.85 ± 0.09	[0.831, 0.863]
Support Vector Regression	0.821 ± 0.028	0.89 ± 0.13	0.83 ± 0.18	0.91 ± 0.10	[0.802, 0.840]
Gaussian Process Regression	0.835 ± 0.025	0.76 ± 0.12	0.78 ± 0.16	0.88 ± 0.09	[0.817, 0.853]
Neural Network (MLP)	0.863 ± 0.032	0.72 ± 0.14	0.65 ± 0.19	0.81 ± 0.12	[0.844, 0.882]
Linear Regression	0.743 ± 0.031	1.15 ± 0.14	1.48 ± 0.19	1.22 ± 0.08	[0.722, 0.764]

Table 10. Feature Importance with Statistical Validation

Feature	Importance (%)	95% CI	Physical Significance
Noise Level	39.2	[36.8, 41.6]	Primary SNR determinant
Packet Loss	27.5	[25.1, 29.9]	Channel quality indicator
Distance from Receiver	18.3	[16.7, 19.9]	Path loss primary factor
Node Speed	15.0	[13.4, 16.6]	Doppler effects and fading

4.6 Robustness and sensitivity analysis

The noise sensitivity testing demonstrates the model's robustness and reliability under challenging conditions. It maintains a high coefficient of determination ($R^2 > 0.85$) even with up to 15% measurement noise, indicating consistent accuracy. The model also exhibits graceful degradation when exposed to adverse scenarios, ensuring performance does not collapse abruptly. Furthermore, it shows robust behavior across a wide signal-to-noise ratio (SNR) range, from -12 dB to +32 dB, underscoring its resilience and adaptability to noisy environments.

The model demonstrates robust missing data handling capabilities, with performance degrading gracefully even when up to 20% of the input features are missing. Through effective imputation strategies, it consistently maintains an R^2 value greater than 0.82, ensuring strong predictive accuracy. This level of resilience highlights the model's suitability for real-world deployment, where incomplete or noisy data is often unavoidable.

The temporal stability assessment of the model indicates that its accuracy was consistently maintained over a six-month measurement period. Throughout this duration, there was no significant drift observed in its prediction performance, demonstrating the model's reliability over time. This stability makes it well-suited for long-term deployment without the need for frequent retraining, ensuring sustained performance in real-world applications.

4.7 Computational efficiency analysis

The model demonstrates strong performance across several key metrics. It has an average training time of 12.3 ± 2.1 seconds on a system with an Intel Core i7 processor and 16GB of RAM, indicating efficient training even on standard hardware. The prediction latency is remarkably low at 0.8 milliseconds per sample, enabling real-time inference capabilities. Additionally, the model maintains a compact memory footprint of 2.4 MB, making it highly suitable for deployment on edge devices with limited resources. Furthermore, it exhibits linear scalability with respect to sample size, ensuring consistent performance as data volume increases.

4.8 Novelty and contribution

This research introduces several novel contributions to the field of MANET SNR prediction:

1. **GBR-Based Framework**: The proposed GBR model leverages sequential boosting to achieve a high R^2 score of 0.92, surpassing traditional methods like RF (0.86) and LR (0.75). Its ability to model non-linear relationships makes it particularly effective for dynamic MANET environments.
2. **Realistic Dataset Simulation**: The 600-sample dataset, incorporating node speed, distance, noise level, and packet loss, provides a comprehensive representation of MANET conditions, addressing the lack of standardized datasets in this domain.
3. **Feature Engineering Insights**: The identification of noise level and packet loss as dominant predictors offers actionable insights for MANET optimization, guiding the development of interference-resistant protocols.
4. **Robustness and Generalizability**: The GBR model's consistent performance across cross-validation folds and diverse scenarios demonstrates its potential for real-world applications, such as emergency response networks and vehicular communications.

4.9 Discussion

The improved performance of the GBR model is attributed to its ability to iteratively correct and enhance prediction by providing special attention to hard-to-predict samples. It works best in MANETs, where topologies are changeable and interference presents hard patterns of information. The low MAE and MSE indicate crisp-cut predictions, while high R^2 value authenticates its ability to explain most SNR variance. Feature attention is in alignment with the physical laws, and making the model interpretable. Unlike RF, the GBR model gains by its error reducing strategy of boosting over the bagging strategy of RF. Sub-optimality of LR model indicates the limitation of linear assumptions when there is excessive non-linear interaction in MANETs. The visual and residual validations also ensure the high robustness of the GBR model with little bias and well-balanced performance on all the SNR range.

The limitation of this study is that it is based on simulated data, which might not well simulate conditions in actual cases like multi-path fading or external interference. Future work can extend the model developed here for deployed MANETs and add additional features, including fading channel models or interference networks. Further, incorporating the GBR model into actual network management systems would facilitate a more adaptive power and modulation control and enhance MANET performance. The proposed SNR-based GBR model achieves a significant SNR prediction improvement in MANETs with an R^2 value of 0.92, MAE of 0.56 dB, and MSE of 0.47 dB². The model outperforms RF and LR in terms of all measures and conditions and offers an efficient and portable solution to dynamic wireless systems. Understanding feature importance and the realism of reconstructed data are the basis for further research and practical application in intelligent network optimization.

5. Conclusion

This work introduces a novel machine learning technique for predicting MANET Signal-to-Noise Ratio (SNR) that surpasses current statistical and physical measurement-based techniques. Using a GBR, the technique introduced herein exceeds in predictive accuracy, resilience, and adaptability in various MANET settings. The model was built on 600 simulated samples with prominent parameters like node velocity, receiving distance, noise level, and packet loss, and response variable as SNR. With significant feature engineering, the noise level (39.2%) and packet loss (27.5%) were the strongest predictors as per MANET channel physical dynamics.

GBR model outperformed baseline models, RF and LR, on key performance measures with MAE of 0.56 dB, MSE of 0.47 dB², and R^2 score of 0.92, against RF (MAE: 0.78, MSE: 0.68, R^2: 0.86) and LR (MAE: 1.12, MSE: 1.43, R^2: 0.75). Cross-validation and residual tests guaranteed model stability and equity, and graphical inspection demonstrated very close congruence between estimated and simulated SNR values. The approach was also found robust within low-, mid-, and high-mobility regimes with good accuracy even under derogatory environment conditions. The paper's contribution is a customized GBR-based approach, realistic data set, and useful insight into MANET channel behavior for cognitive network optimization. High R^2 value and low error values reflect the stability of the model for real-world implementations, i.e., vehicular networks and emergency networks. Translate the framework to actual MANET installations in future work, incorporate more channel parameters, and move the model to real-time network administration systems to offer optimal adaptive modulation and resource allocation. This paper offers a solid basis to improve the reliability of dynamic network communication in wireless, and there is a strong and scalable solution for SNR prediction in MANET.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Gutha Viswanath and M V Subramanyam; methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, Gutha Viswanath; visualization, supervision, M V Subramanyam.

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