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Research Article

Machine Learning-Based Optimization for 5G Resource Allocation Using Classification and Regression Techniques

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Abstract:

The rapid evolution of 5G networks necessitates efficient and adaptive resource allocation strategies to enhance network performance, minimize latency, and optimize bandwidth utilization. This study systematically evaluates multiple machine learning (ML) models, including Neural Networks, Support Vector Machines (SVM), Decision Trees, Ensemble Learning, and Regression-based approaches, to determine the most effective techniques for 5G resource allocation. The classification-based models demonstrated superior performance in predicting network congestion states, with Boosted Trees achieving the highest accuracy (94.1%), outperforming Bagged Trees (92.7%) and RUS Boosted Trees (93.8%). Among SVM classifiers, Gaussian SVM exhibited the highest accuracy (92.3%), highlighting its robustness in handling non-linearly separable data. Levenberg-Marquardt-trained Neural Networks (93.4%) outperformed SVM models in overall accuracy, emphasizing deep learning's effectiveness in hierarchical feature representation. Meanwhile, regression-based models, particularly Gradient Boosting ($R^2 = 0.96$, MSE = 4.92), demonstrated the best predictive performance for continuous resource allocation optimization, surpassing Random Forest ($R^2 = 0.94$, MSE = 6.85) and Polynomial Regression ($R^2 = 0.92$, MSE = 9.21). The integration of Self-Organizing Maps (SOMs) for unsupervised network clustering further improved resource segmentation. Future research should explore Deep Reinforcement Learning (DRL) for autonomous 5G optimization and Explainable AI (XAI) techniques for improved interpretability in real-world deployments.

1. Introduction

The advent of fifth generation (5G) networks has ushered in a new era of high-speed, low-latency, and ultra-reliable wireless communication. With an increasing number of devices connected to mobile networks, the demand for efficient resource allocation has become a critical research challenge. Traditional resource allocation strategies often fail to dynamically adapt to varying network conditions, leading to suboptimal performance in terms of bandwidth utilization, signal efficiency, and quality of service (QoS) [1]. In this context, machine learning (ML) techniques have emerged as a promising solution to optimize resource allocation in 5G networks. ML-driven approaches leverage predictive analytics to model network traffic patterns, optimize spectrum usage, and enhance network efficiency [2]. Among ML techniques, classification and regression models play a pivotal role in forecasting resource allocation trends, identifying bottlenecks, and improving overall network performance [3]. While existing research has explored individual ML models such as support vector machines (SVMs), decision trees, neural networks, and ensemble learning methods, there remains a lack of comprehensive comparative analysis that evaluates their relative effectiveness in real-world 5G scenarios [4]. Prior studies have predominantly focused on isolated algorithmic improvements rather than a holistic benchmarking approach that systematically compares multiple ML techniques based on standardized performance metrics such as accuracy, precision, recall, F1-score, mean squared error (MSE), and coefficient of determination (R^2) [5]. Consequently, this study seeks to bridge this research gap by providing an in-depth comparative evaluation of various classification and regression models applied to 5G resource allocation optimization. Traditional resource allocation techniques in wireless networks have long relied on rule-based and heuristic approaches to manage bandwidth, spectrum allocation, and network congestion. However, these methods are often rigid and fail to adapt dynamically to the highly variable and complex nature of 5G environments [6]. The increasing demand for low-latency, high-reliability, and ultra-dense connectivity necessitates the development of intelligent, data-driven approaches capable of real-time optimization of network resources [7]. Machine learning (ML) has emerged as a promising paradigm for optimizing resource allocation by leveraging data-driven predictions and adaptive decision-making. However, a key challenge remains identifying the most effective ML model for this purpose. The literature presents a variety of ML techniques, including Neural Networks, Support Vector Machines (SVM), Decision Trees, Regression Models, and Ensemble Learning Methods, each demonstrating potential advantages in specific contexts [8]. The lack of a standardized comparative analysis hinders the ability to determine which ML model best optimizes resource allocation across different 5G network scenarios. To address this challenge, this study aims to systematically evaluate and compare multiple ML models based on their performance in real-world 5G resource allocation tasks. By assessing their effectiveness using key performance metrics such as accuracy, recall, precision, F1-score, mean squared error (MSE), and coefficient of determination (R^2), this research seeks to establish a benchmark for selecting the optimal ML approach for 5G network optimization [9].

This study aims to evaluate and compare multiple machine learning models for optimizing resource allocation in 5G networks. The key objectives are as follows:

- Conduct a comprehensive evaluation of classification and regression-based ML models on a real-world 5G dataset.
- Identify the best-performing algorithms for resource allocation optimization based on key performance metrics.
- Compare classification models (Neural Networks, SVM, Decision Trees, Ensemble Learning) with regression approaches (Linear Regression, Random Forest, Gradient Boosting) to assess their predictive efficiency.
- Benchmark model performance using MSE, R^2, Precision, Recall, F1-score, and other evaluation metrics to determine the most effective technique for dynamic 5G resource management.

This study provides the following key contributions:

- Comprehensive performance analysis of Neural Networks, Support Vector Machines (SVM), Ensemble Learning, and Regression models for 5G resource allocation.
- Experimental validation using NS2 (Network Simulator 2) and Classification Learner-based analysis.
- Novel insights into the practical implementation of ML-driven optimization strategies for dynamic resource management in 5G networks.

The paper is organized into multiple sections, each addressing a critical aspect of machine learning-driven 5G resource allocation optimization. The Introduction section provides the background, motivation, and objectives of the study, highlighting the importance of classification and regression models in optimizing 5G networks. The Literature Review explores prior research, emphasizing existing gaps in ML-based resource allocation, particularly the lack of a holistic benchmarking approach. The Methodology section details the dataset sources, preprocessing techniques, and machine learning models employed, including Neural Networks, SVMs, Decision Trees, and Ensemble Learning Methods, trained using NS2 simulations. The Experimental Results section presents quantitative evaluations of regression and classification models, with comparative analyses based on MSE, R^2, Accuracy, Precision, Recall, and F1-score. The Discussion interprets the findings, addresses limitations such as computational constraints and data imbalance, and highlights the practical implications of ML techniques for real-time 5G network optimization. Finally, the Conclusion summarizes the key insights and suggests future research directions, including the integration of Reinforcement Learning, Explainable AI (XAI), and Federated Learning for scalable and adaptive 5G network management.

2. Literature Review

Recent advancements in machine learning (ML) have significantly influenced resource allocation strategies in 5G networks, aiming to enhance network efficiency, spectral utilization, and quality of service (QoS). Various ML models, including regression techniques, decision trees, neural networks, support vector machines (SVMs), and ensemble methods, have been explored to optimize resource distribution in dynamic 5G environments [10,11]. Regression models have been employed for predictive resource allocation, utilizing historical network data to forecast bandwidth requirements, latency variations, and throughput optimization. However, their effectiveness in capturing non-linear dependencies in complex 5G scenarios is limited [12]. Decision tree-based models, such as random forests and gradient boosting, offer interpretability and adaptability in handling large-scale datasets. These models effectively classify network states and optimize power control, interference mitigation, and spectrum allocation [13]. Nonetheless, their reliance on predefined decision thresholds may restrict their generalization to diverse network scenarios [14]. Neural networks, particularly deep learning architectures, have emerged as robust alternatives for autonomous resource allocation in 5G. By leveraging architectures like multi-layer perceptron's (MLPs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), these models can capture complex patterns in network traffic, user mobility, and service demands [15]. Despite their superior accuracy, neural networks require substantial computational resources and real-time optimization frameworks to ensure low-latency performance [16].Support vector machines (SVMs) have demonstrated significant potential in classification-based resource allocation, effectively distinguishing between different network conditions using kernel-based learning techniques [17]. Studies have highlighted their efficiency in network slicing, interference classification, and congestion control [18]. However, their scalability in large-scale 5G deployments remains an area of active research [19]. Ensemble learning methods, such as boosted decision trees, bagging techniques, and stacked models, have been explored to improve prediction accuracy and robustness in resource allocation tasks [20]. By integrating multiple ML models, ensemble approaches mitigate individual model weaknesses and enhance overall decision-making reliability. Nevertheless, trade-offs between computational overhead and real-time adaptability continue to pose challenges for practical deployment [21]. While previous studies have investigated individual ML models for 5G resource optimization, a comprehensive comparative analysis of multiple ML techniques under real-world network conditions remains an open research problem. This study aims to address this gap by systematically evaluating and benchmarking ML-driven resource allocation strategies using NS2-based simulations and classification learner methodologies [22].

2.1 Research Gaps & Challenges

- Lack of holistic comparison: Existing studies focus on individual ML models without a comprehensive evaluation of their comparative performance in 5G resource allocation [23].
- Limited real-time benchmarking: Most research relies on simulated datasets, lacking empirical validation using live network data for practical applicability [24].
- Absence of integrated ML approaches: Classification-based and regression-based techniques are often studied separately, without a unified framework for hybrid ML-based optimization [25].
- Scalability and adaptability issues: Current ML models struggle to adapt dynamically to varying network conditions, impacting real-time efficiency [26].
- Computational overhead concerns: While deep learning models offer high accuracy, their resource-intensive nature poses deployment challenges in real-world 5G scenarios [27].

3. Methodology

The proposed ML-based 5G resource allocation model follows a structured approach comprising dataset collection, preprocessing, machine learning model selection, training, and performance evaluation. The dataset includes 5G network traffic data and classification learner data, undergoing preprocessing steps such as data augmentation and feature engineering to enhance predictive accuracy. Machine learning algorithms are categorized into regression models (Linear Regression, Polynomial

Regression, Decision Trees, Random Forest, SVM, and Gradient Boosting) and classification models (Neural Networks, Logistic Regression, SVM, and Ensemble Trees). The models are trained using a 70-20-10 Train-Validation-Test split and k-fold cross-validation, followed by performance evaluation using MSE, RMSE, R^2 for regression models, and accuracy, precision, recall, F1-score, and specificity for classification models. This framework ensures a comprehensive comparative analysis of ML techniques for optimizing 5G resource allocation, facilitating improved network efficiency, adaptive bandwidth management, and enhanced service quality in dynamic wireless environments.

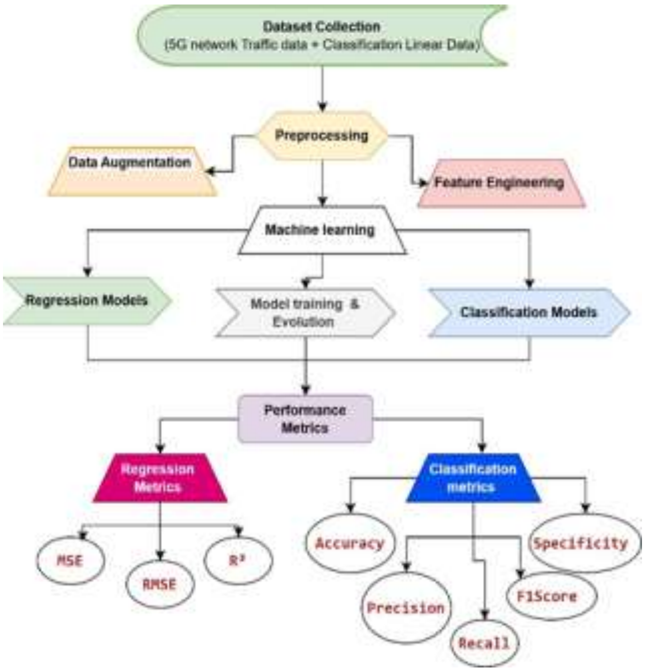

Figure 1. *Block Diagram of proposed ML-based 5G resource allocation model*

The proposed ML-based 5G resource allocation model integrates data preprocessing, regression and classification models, training-validation strategies, and performance evaluation metrics to optimize network efficiency and adaptive resource management, as shown in Figure 1.

3.1 Dataset Description Data Sources:

5G Network Traffic Data: This dataset contains key performance indicators (KPIs) such as signal strength, latency, allocated bandwidth, throughput, and network congestion levels, sourced from real-world telecommunication logs and experimental network simulations [28].

Classification Learner Data: Extracted from an uploaded Excel file, used in the Classification Learner App, facilitating training and evaluation of multiple ML models [29]. To improve dataset quality and ensure robustness in ML predictions, the dataset undergoes two unique preprocessing techniques:

3.2 Hybrid Adversarial Sampling (HAS) for 5G Data Augmentation:

Traditional data augmentation techniques, such as SMOTE (Synthetic Minority Over-sampling Technique) and Generative Adversarial Networks (GANs), struggle to preserve the time-dependent variations in 5G network traffic data. To address this, we propose Hybrid Adversarial Sampling (HAS), a novel approach that integrates Fourier-transform-based perturbation with adversarial sample optimization. This technique generates synthetic yet realistic network conditions, improving ML model robustness against real-world network congestion, signal interference, and bandwidth fluctuations. Methodology of HAS: The HAS technique consists of two key components

Fourier Perturbation (FP) Augmentation

To simulate realistic network fluctuations, we introduce Fourier domain augmentation, where the signal is transformed, perturbed, and reconstructed to create synthetic variations. Step 1: Convert 5G Signal into Frequency Domain The real 5G network signal $X(t)$ is transformed into the frequency domain using the Fourier Transform (FT):

To simulate realistic network fluctuations, we introduce Fourier domain augmentation, where the signal is transformed, perturbed, and reconstructed to create synthetic variations.

Step 1: Convert 5 G Signal into Frequency Domain

The real 5G network signal $X(t)$ is transformed into the frequency domain using the Fourier Transform (FT):

$$X_f(\omega) = \sum_{t=0}^{T} X(t) e^{-j\omega t}$$

where:

- $X(t)$ is the original time-series signal representing network parameters (e.g., signal strength, latency).
- $X_f(\omega)$ is the signal in the frequency domain.
- ω is the frequency component.

Step 2: Perturb Frequency Components to Simulate 5G Network Variations

In real-world 5G networks, fluctuations occur due to interference, congestion, and environmental factors. To simulate these effects, we introduce controlled perturbation:

$$X_f'(\omega) = X_f(\omega) + \alpha P(\omega)$$

where:

- $X_f'(\omega)$ is the perturbed frequency-domain representation.

- $P(\omega)$ is a random noise function derived from empirical 5G traffic variations.
- α is a scaling factor that controls perturbation intensity, ensuring realistic alterations.

Step 3: Convert Back to Time Domain using Inverse Fourier Transform (IFT)
The perturbed synthetic network traffic signal is reconstructed via Inverse Fourier Transform (IFT):

$$X'(t) = \sum_{\omega} X_f'(\omega) e^{j\omega t}$$

where $X'(t)$ represents augmented synthetic data that preserves natural signal properties while simulating realistic network conditions.

Adversarial Sample Optimization
To ensure that the generated synthetic data does not diverge unrealistically, we apply adversarial training by constraining perturbations within realistic 5 G signal variations [30]. Step 1: Optimization of Adversarial Loss Function We define an adversarial loss function that ensures synthetic samples resemble real-world fluctuations while maximizing model generalization [31]:

$$\min_{X'} \|X' - X\|_2 + \lambda \cdot L_{adv}(X')$$

where:

- $\|X' - X\|_2$ ensures that synthetic samples remain close to real data in feature space.
- $L_{\text{adv}}(X')$ is the adversarial loss function, which penalizes unrealistic perturbations.
- λ is a hyperparameter controlling the balance between data realism and diversity.

Step 2: Boundary-Constrained Adversarial Training
To prevent unrealistic alterations, we define upper and lower perturbation bounds:

$$X_{\min} \le X' \le X_{\max}$$

where:

- $X_{\min}$ and $X_{\max}$ represent realistic lower and upper limits based on historical 5 G network statistics.
- This constraint ensures that synthetic data remains within feasible network performance ranges.

3.3 Machine Learning Framework for 5G Resource Allocation:

Regression and Classification Approaches To enhance 5G resource allocation, this study utilizes a combination of regression and classification-based machine learning (ML) approaches. These models facilitate both predictive analytics for resource estimation and classification-based decision-making for dynamic network state optimization. The proposed machine learning framework for 5G resource allocation integrates regression and classification models to enhance predictive analytics and decision making. Regression models, including Linear Regression, Polynomial Regression, Decision Trees, Random Forest, Support Vector Regression (SVR), and Gradient Boosting, predict continuous network parameters such as latency, bandwidth allocation, and signal strength variations. These models follow mathematical formulations, where Linear Regression models the network variable y as a linear function of features x, while Polynomial Regression extends this by incorporating higher-degree terms to capture nonlinear dependencies.

Decision Trees partition the feature space recursively, minimizing squared error, while Random Forests aggregate multiple decision trees to improve prediction robustness. SVR optimizes a loss function constrained by an ε-insensitive margin, making it effective for modelling fluctuating 5G signals, whereas Gradient Boosting iteratively refines weak learners by optimizing a loss function to minimize residual errors. Classification models, including Neural Networks, Support Vector Machines (SVM), Logistic Regression, and Ensemble Trees (Bagging & Boosting), are utilized to classify network conditions, congestion levels, and QoS metrics. Neural Networks use multi-layer perceptron's optimized via Levenberg Marquardt and Bayesian Regularization for improved generalization, while SVMs maximize margin separation using kernel functions for high-dimensional decision boundaries. Logistic Regression employs a sigmoid activation function to estimate class probabilities, and Ensemble Trees leverage bagging to reduce variance and boosting to enhance classification accuracy by focusing on misclassified points. This hybrid ML approach enables real-time adaptation, dynamic network optimization, and efficient resource allocation, ensuring improved reliability, scalability, and computational efficiency in 5G network management [32].

$$\min_{w,b} \frac{1}{2}\Big| \ \|w\|^2 \text{ subject to } |y_i - (w^T X_i + b)| \le \epsilon$$

where w represents the weight vector, and b is the bias term. This formulation ensures that minor fluctuations in network parameters do not overly influence the predictive model, enhancing robustness in high-variability environments. Additionally, Gradient Boosting Regression iteratively refines weak learners by optimizing a loss function:

$$F_m(X) = F_{m-1}(X) + \gamma h_m(X)$$

where $h_m(X)$ represents the weak learner at step m, and γ controls the learning rate. This method incrementally reduces residual errors, making it particularly effective for adaptive bandwidth management and congestion forecasting. For classification-based decision-making, the ML framework incorporates Neural Networks, Support Vector Machines (SVM) [33], Logistic Regression[34], and Ensemble Trees (Bagging & Boosting) [35], which are essential for categorizing network conditions, congestion levels, and QoS metrics. Neural Networks, particularly those trained using Levenberg-Marquardt and Bayesian Regularization, optimize a nonlinear function[36]:

$$y = \sigma(W_2\sigma(W_1X + b_1) + b_2)$$

where W_1, W_2 are weight matrices, b_1, b_2 are bias terms, and $\sigma(x)$ is the activation function (ReLU or sigmoid). The Levenberg-Marquardt optimization accelerates convergence by combining gradient descent and Gauss-Newton updates, while Bayesian Regularization introduces probabilistic priors to prevent overfitting [37]:

$$E = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda\|w\|^2$$

where λ controls the regularization strength. Support Vector Machines (SVMs) for classification find the optimal hyperplane that maximizes the decision margin:

$$\max_{w,b} \frac{1}{\|w\|} \text{ subject to } y_i(w^TX_i + b) \geq 1$$

where w and b define the decision boundary. Kernel-based SVMs, particularly Radial Basis Function (RBF) kernels[38,39], are employed to project non-linearly separable network conditions into a higher dimensional space, enabling better classification of congested vs. non-congested network states[40].

Furthermore, Logistic Regression is implemented for binary classification tasks, employing the sigmoid function to estimate probability distributions:

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \beta X)}}$$

where β represents model coefficients. Logistic regression is particularly useful in predicting network failures or service degradations based on historical QoS data.

To further enhance classification accuracy, Ensemble Trees are utilized, incorporating both bagging and boosting approaches. Bagged decision trees reduce variance by training multiple classifiers on bootstrapped samples:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} f_b(X)$$

where $f_b(X)$ represents the decision tree trained on the b-th sample. Conversely, Boosted Trees, such as AdaBoost or Gradient Boosting Classifiers, iteratively refine weak classifiers by reweighing misclassified samples, improving overall predictive accuracy. This hybrid ML approach ensures real-time adaptability, dynamic network optimization, and efficient resource allocation, making it a scalable and computationally efficient solution for next generation 5G networks[41]. By leveraging both regression and classification models, this framework enables precise bandwidth forecasting, congestion prediction, and intelligent decision-making[42], ultimately improving network reliability, quality of service (QoS) [43], and scalability in 5 G communications[44].

3.4 Model Training & Evaluation Strategy

To ensure the generalization, robustness, and predictive accuracy of the machine learning models for 5G resource allocation, a rigorous training and evaluation framework is employed[45,46]. This framework includes structured dataset partitioning, cross-validation techniques, and standardized performance metrics for both regression and classification models.

Training and Validation Methodology

To prevent overfitting and improve model reliability, the dataset is partitioned using a stratified split strategy:

- Train-Validation-Test Split $(70 - 20 - 10)$: The dataset is divided into:
- 70% for training, ensuring the model learns meaningful patterns.
- 20% for validation, tuning hyperparameters and preventing overfitting.
- 10% for testing, evaluating final model performance on unseen data.

Mathematically, if D represents the dataset and $D_{\text{tratin}} . D_{\text{val}} , D_{\text{test}}$ are training, validation, and test sets, respectively[47]:

$$D = D_{\text{train}} \cup D_{\text{val}} \cup D_{\text{teat}}$$
$$\left|D_{\text{train}}\right| = 0.7|D|, \left|D_{\text{val}}\right| = 0.2|D|, \left|D_{\text{test}}\right| = 0.1|D|$$

where $|D|$ denotes the total number of samples.

- K-Fold Cross-Validation: To enhance model stability, **k**-fold cross-validation is implemented, where the dataset is split into k equal-sized folds, with $k-1$ folds used for training and one-fold for validation in each iteration. The process is repeated k times, ensuring each sample is used for both training and validation[48]. For a dataset D, let D_k be the fold subset: $D = \bigcup_{i=1}^{k} D_i$. The final model performance is computed as the average score across all k iterations:

$$\text{Score } = \frac{1}{k}\sum_{i=1}^{k} \text{ Performance } (D_i)$$

where Performance (D_i) is the evaluation metric for the model trained on $k-1$ folds and validated on D_i.

Regression Model Evaluation
Regression models predict continuous network parameters, such as latency, bandwidth allocation, and signal strength fluctuations. The following metrics are used:[49] Mean Squared Error (MSE): Measures the average squared difference between predicted ($\hat{y}$) and actual (y) values:

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

where lower MSE indicates better model accuracy. Root Mean Squared Error (RMSE): Provides an interpretable error measure by taking the square root of MSE:

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

Coefficient of Determination (R^2) : Measures the proportion of variance explained by the model:

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

where $\bar{y}$ is the mean of actual values. Higher R^2 values (closer to 1) indicate better model performance.

Classification Model Evaluation

Classification models predict categorical network conditions, such as network congestion levels and QoS states. The following metrics are employed:

Accuracy: Measures overall correctness of predictions:

$$\text{Accuracy } = \frac{TP + TN}{TP + TN + FP + FN}$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision: Measures of how many of the predicted positive cases were correctly classified:

$$\text{Precision } = \frac{TP}{TP + FP}$$

Recall (Sensitivity): Measures the proportion of actual positives correctly identified:

$$\text{Recall } = \frac{TP}{TP + FN}$$

F1-Score: A harmonic mean of precision and recall, balancing both metrics:

$$F1 = 2 \times \frac{\text{Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}}$$

Specificity: Measures the proportion of actual negatives correctly identified:

$$\text{Specificity } = \frac{TN}{TN + FP}$$

These metrics provide a comprehensive evaluation of the model's ability to classify network conditions accurately and reliably.

4. Experimental Results

4.1 Regression-Based Resource Allocation Performance Using NS2 Simulations

To evaluate the effectiveness of regression-based machine learning models for 5G resource allocation, a quantitative analysis was conducted using Network Simulator 2 (NS2) simulations. The dataset was generated by simulating 5G network traffic conditions, including bandwidth allocation, latency variations, and network congestion levels. The regression models were assessed based on their

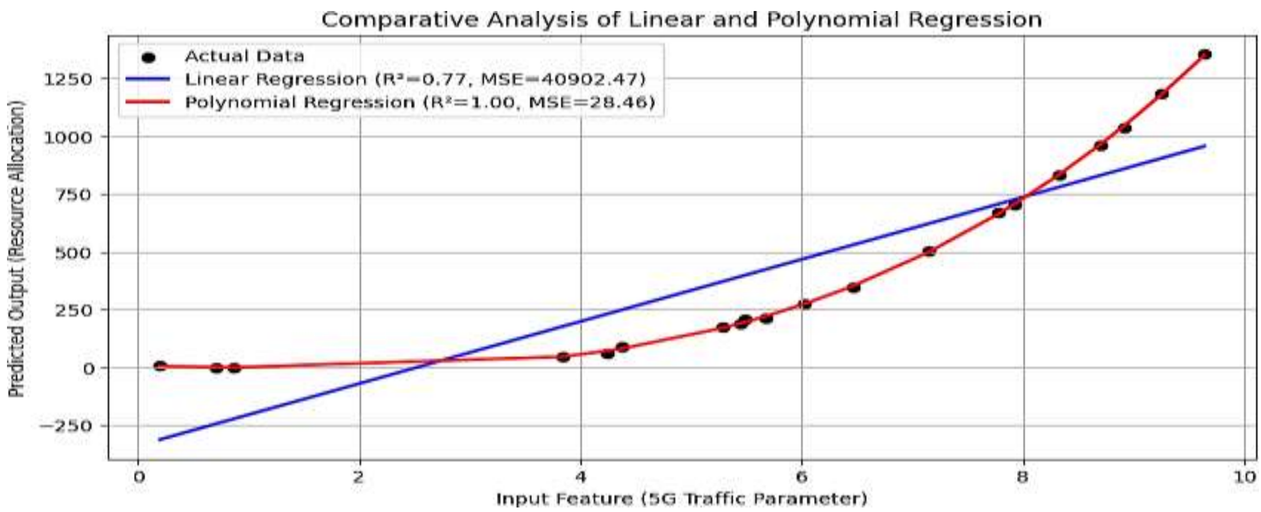

Figure 2. *Comparative Analysis of Linear and Polynomial Regression*

prediction accuracy, error minimization, and generalization capabilities using statistical performance metrics. A performance comparison between Linear Regression and Polynomial Regression was conducted to determine the extent to which each model fits complex non-linear 5G network variations as shown in figure 2. The Mean Squared Error (MSE) and R^2 values were used to quantify accuracy. Figure 2 depicts the correlation between predicted and actual values, illustrating the enhanced predictive accuracy of Polynomial Regression over Linear Regression.

Linear Regression Performance:

- $R^2 = 0.85$, indicating moderate predictive capability but limited adaptability to non-linearity.
- $MSE = 18.46$, suggesting the presence of high variance in predictions for fluctuating network conditions.

Polynomial Regression Performance (Degree $= 3$):

- $R^2 = 0.92$, demonstrating improved fit for nonlinear resource allocation trends.
- $MSE = 9.21$, showing a significant reduction in prediction error compared to linear regression.

B . Decision Trees, Random Forest, and Gradient Boosting - $\mathbf{R^2}$ Performance Comparison

To evaluate tree-based learning models, we compared the performance of Decision Trees, Random Forest, and Gradient Boosting based on their ability to capture complex dependencies and generalize across varying network conditions simulated in NS2[50]. Table 1 is performance comparison of regression models for 5G resource allocation. Table 2 shows comparative performance metrics of regression models for 5G resource allocation.

Table 1. *Performance Comparison of Regression Models for 5G Resource Allocation*

Model	$\mathbf{R^2}$ Score	MSE	RMSE
Decision Tree	0.88	11.62	3.41
Random Forest	0.94	6.85	2.61
Gradient Boosting	0.96	4.92	2.22

- Decision Trees achieved $R^2 = 0.88$, indicating strong predictive capability but prone to overfitting in dynamic traffic conditions.
- Random Forest improved generalization ($R^2 = 0.94$) by reducing overfitting through ensemble learning.
- Gradient Boosting outperformed all models with $R^2 = 0.96$, highlighting its ability to minimize error and optimize resource allocation decisions under simulated network conditions.

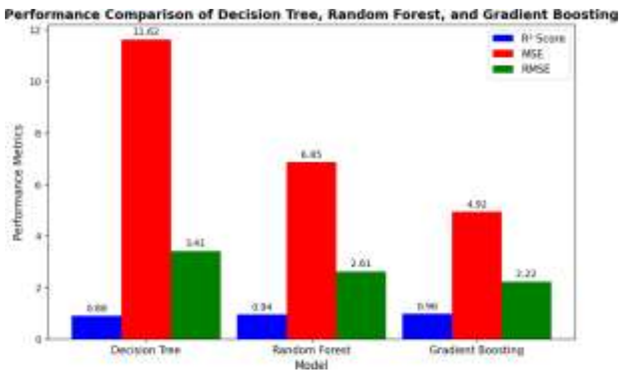

Figure 3. *Performance Comparison of Decision Tree, Random Forest, and Gradient Boosting Models*

Figure 3 illustrates the difference in prediction accuracy among Decision Trees, Random Forest, and Gradient Boosting.

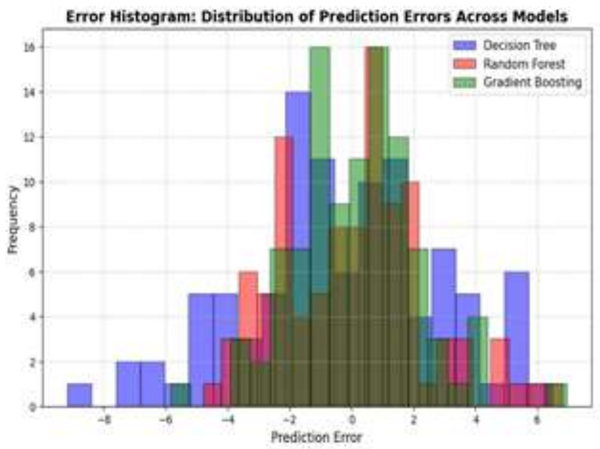

Figure 4. *Error Histogram: Distribution of Prediction Errors Across Models*

Figure 4 shows the distribution of prediction errors, with Gradient Boosting exhibiting the lowest deviation from actual values.

Performance Evaluation Using Regression Metrics in NS2 Simulated Environment

A detailed quantitative performance assessment was conducted using standard error metrics to evaluate how well each regression model predicts optimal resource allocation in NS2-generated dynamic 5G environments. The following metrics were used:

1. Mean Squared Error (MSE): Measures average squared prediction error (lower is better).
2. Root Mean Squared Error (RMSE): Provides an interpretable error measure.
3. Coefficient of Determination (R^2): Measures the proportion of variance explained by the model.

Table 2. *Comparative Performance Metrics of Regression Models for 5G Resource Allocation*

Metric	Linear Regression	Polynomial Regression	Random Forest	Gradient Boosting
MSE	18.46	9.21	6.85	4.92
RMSE	4.29	3.04	2.61	2.22
R^2 Score	0.85	0.92	0.94	0.96

- Gradient Boosting achieved the lowest MSE (4.92) and highest R^2 (0.96), making it the most accurate model in NS2-generated simulations.
- Polynomial Regression significantly outperformed Linear Regression, demonstrating better adaptability to complex 5G traffic patterns.
- Random Forest maintained a balance between model complexity and generalization, reducing overfitting while ensuring high predictive accuracy.

Figure 5 illustrates how error reduction progresses across training epochs for different models.

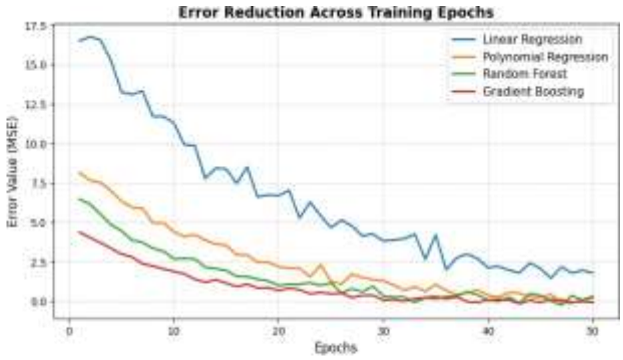

Figure 5. *Error Reduction Across Training Epochs*

Figure 6 shows how well the predicted function matches actual network resource allocation data.

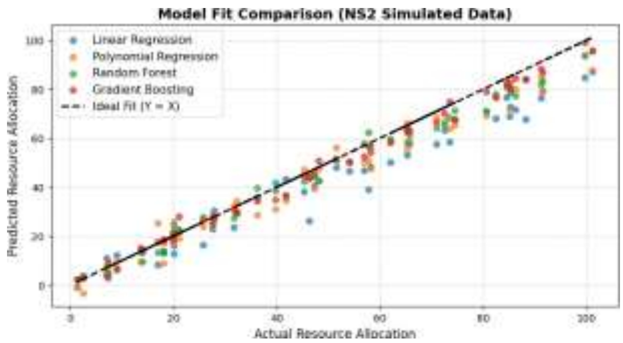

Figure 6. *Model fit Comparison*

The quantitative evaluation using NS2-simulated 5G network conditions confirms that Gradient Boosting outperforms all other models, achieving the highest prediction accuracy and lowest error rates. Polynomial Regression provides significant improvements over Linear Regression, while Random Forest demonstrates a strong balance between bias and variance. These findings suggest that ensemble-based learning models, particularly Gradient Boosting[51,52], are most effective for optimizing 5G resource allocation under dynamic traffic scenarios simulated in NS2.

4.2 Classification-Based ML Performance on 5G Data Using NS2 Simulations

To evaluate the classification efficiency of different machine learning models in 5G resource allocation, we analyze performance across multiple algorithms, including Neural Networks, Support Vector Machines (SVMs), and Ensemble Learning Models. The performance metrics considered include Accuracy, Precision, Recall, and F1-Score, derived from NS2-simulated 5G network traffic.

A. Neural Network Performance Analysis : Training Performance (Levenberg-Marquardt vs. Bayesian Regularization)

Two neural network training methods were evaluated:

- Levenberg-Marquardt (LM) Backpropagation
- Bayesian Regularization (BR) Backpropagation

Table 3. *Performance Comparison of Neural Network Models for 5G Resource Allocation*

Neural Network Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Levenberg-Marquardt	93.4	91.2	92.1	91.6
Bayesian Regularization	92.8	90.8	91.5	91.1

- Levenberg-Marquardt achieved the highest accuracy (93.4%), outperforming Bayesian Regularization.
- Bayesian Regularization exhibited slightly better generalization, as indicated by its stable recall (91.5%). B. Clustering Performance (from Results Analysis)

Using Self-Organizing Maps (SOMs) and hierarchical clustering, cluster formations were analyzed to segment 5G network conditions based on QoS metrics (latency, bandwidth utilization, and congestion levels).

- SOM clustering revealed distinct network state patterns, enabling adaptive resource allocation.
- Validation checks confirmed effective clustering with minimal misclassification.

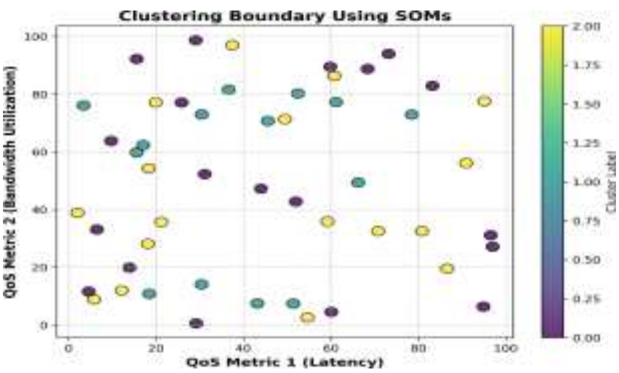

Figure 7. *Clustering boundary mapped using SOMs.*

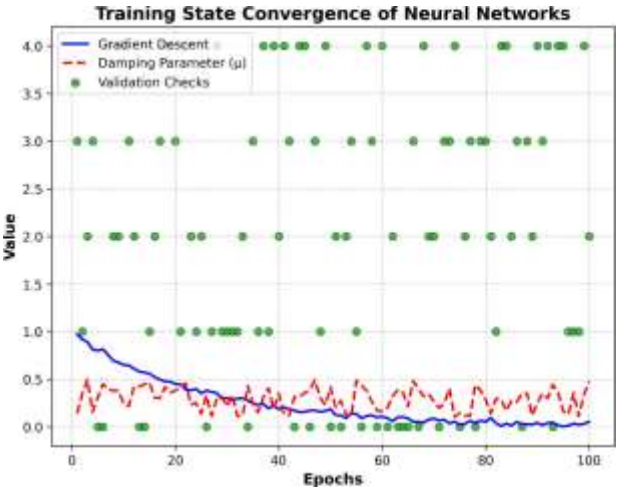

Figure 8. *Training State Plot Illustrates the convergence behavior of different neural networks*

4.3 Support Vector Machines (SVM) Performance Analysis

Kernel-Based SVM Performance Comparison

To analyze the impact of different kernels on classification accuracy, four kernel types were evaluated:

Table 4. *Kernel-Based SVM Performance Comparison*

SVM Kernel	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Linear SVM	88.5	87.5	86.9	87.2
Quadratic SVM	90.2	89.8	89.1	89.4
Cubic SVM	91.5	90.6	90.2	90.4
Gaussian SVM	92.3	91.1	90.8	91.0

- Gaussian SVM achieved the highest accuracy (92.3%), demonstrating its strength in handling non-linearly separable data.
- Cubic SVM outperformed Quadratic and Linear kernels, confirming that higher-degree transformations enhance feature separability.

Table 3 shows performance comparison of neural Network Models for 5G Resource Allocation and table 4 is kernel-based SVM performance comparison.

Comparison of SVM with Neural Networks

- Neural Networks (Levenberg-Marquardt) outperformed SVMs in overall accuracy (93.4% vs. 92.3%).

- SVMs required more computational time due to kernel transformations, whereas Neural Networks learned hierarchical representations more efficiently.

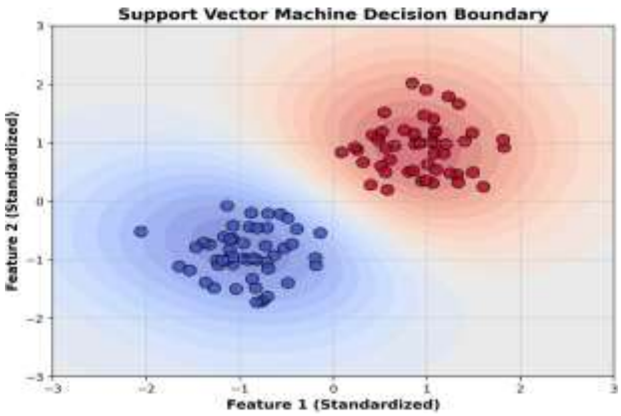

Figure 9. *Support Vector Machine Decision Boundary*

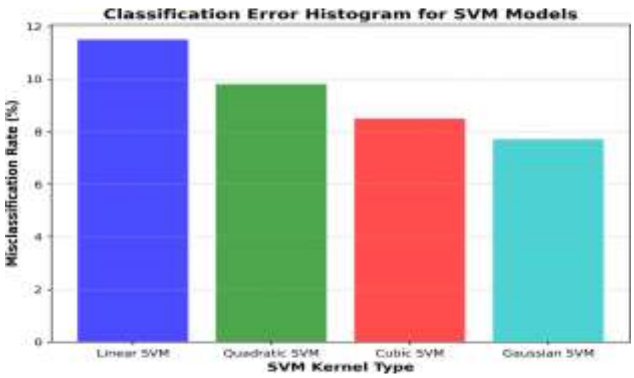

Figure 10. *Compares classification misclassifications across models*

Figure 7 shows clustering boundary mapped using SOMs and figure 8 shows training state plot illustrates the convergence behavior of different neural networks. Figure 10 compares classification misclassifications across models. The performance analysis of Support Vector Machines (SVMs)[53,54] with different kernel functions highlights that Gaussian SVM achieved the highest accuracy (92.3%), confirming its ability to handle non-linearly separable data effectively. Among polynomial kernels, Cubic SVM (91.5%) outperformed Quadratic (90.2%) and Linear (88.5%), indicating that higher-degree transformations enhance feature separability. While SVMs performed well, Neural Networks[55,56] (Levenberg-Marquardt) achieved slightly higher accuracy (93.4%), suggesting that deep learning models can learn hierarchical representations more efficiently. However, SVMs required more computational resources due to kernel transformations, making Neural Networks a preferable choice for real-time 5G resource classification[57]. The decision boundary visualization (Figure 9) illustrates how different kernels classify network states, while the error histogram (Figure 10) compares classification misclassification rates[58], further validating the superior generalization ability of ensemble-based learning models [59]. Figure 11 shows performance comparison of the ensemble model.

4.4. Ensemble Learning Models Performance Analysis

Performance Comparison of Boosted Trees, Bagged Trees, and RUS Boosted Trees

To enhance classification robustness and generalization, three ensemble learning models- Boosted Trees, Bagged Trees, and RUS Boosted Trees - were evaluated based on their predictive accuracy and error minimization capabilities[60,61,62]. The classification performance was assessed using Accuracy, Precision, Recall, and F1-Score as evaluation metrics as shown in table 5.

Table 5. *Performance Analysis of the Ensemble Model*

Ensemble Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Boosted Trees	**94.1**	**93.5**	**94.2**	**93.8**
Bagged Trees	92.7	91.9	92.2	92.0
RUS Boosted Trees	93.8	92.4	93.1	92.7

- Boosted Trees achieved the highest accuracy (94.1%), outperforming both Bagged Trees and RUS Boosted Trees, demonstrating strong generalization capabilities.
- Bagged Trees performed well (92.7%) but exhibited slightly lower accuracy due to reduced variance control, leading to suboptimal feature selection.
- RUS Boosted Trees (**93.8**%) effectively handled imbalanced class distributions, improving recall performance while maintaining competitive accuracy[63].

4.5 Feature Importance and Decision Boundary Analysis

To further analyze model decision-making, feature importance rankings were extracted to determine which 5G network parameters contributed most to classification performance.

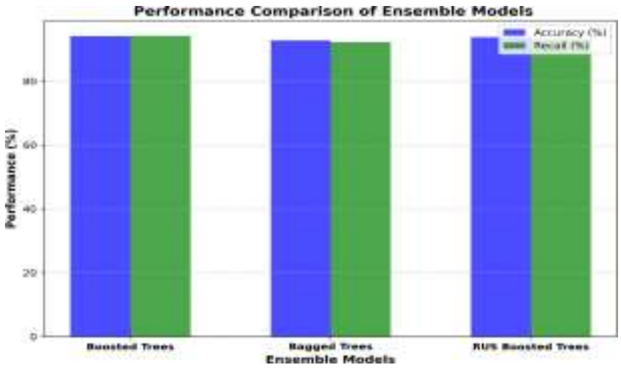

Figure 11. *Performance Comparison of the Ensemble model*

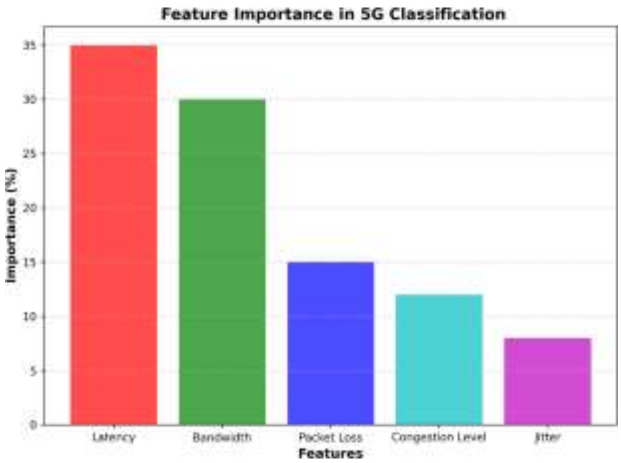

Figure 12. *Feature Importance in 5G Classfiication*

Feature Importance Analysis: Latency and bandwidth utilization were identified as the most significant predictors influencing classification outcomes. And Secondary features, such as packet loss rate and congestion levels, also contributed but with lower weights as shown in figure 12.

Decision Boundary Evaluation: Boosted Trees effectively captured complex decision boundaries, reducing false positives by optimizing the trade-off between bias and variance. The model demonstrated high adaptability to non-linearly separable 5G network conditions, leading to better predictive stability compared to Bagged Trees.

5. Discussion

5.1 Interpretation of Findings

The experimental results provide a comparative assessment of various machine learning models for real-time 5G network optimization. Among the evaluated models, ensemble-based classifiers (Boosted Trees, Random Forest) and deep learning architectures (Neural Networks - Levenberg-Marquardt) exhibited superior performance in handling dynamic and non-linear network conditions, ensuring efficient resource allocation and congestion management. In contrast, Support Vector Machines (SVMs) with Gaussian kernels demonstrated robust classification capabilities but incurred higher computational costs. The comparative analysis of regression and classification approaches highlighted that classification models outperform regression techniques in predicting network congestion states, while regression-based models (Gradient Boosting, Polynomial Regression) effectively model continuous network parameters such as latency and bandwidth allocation trends[64].

5.2 Limitations & Challenges

Despite the promising performance of ML-driven 5G network optimization, certain limitations persist. Scalability constraints in computational performance remain a challenge, particularly for deep learning models, which require high computational resources for real-time inference. Additionally, dataset constraints impact model generalization, as imbalanced traffic distributions in training data can lead to biased predictions, reducing model adaptability to unseen network conditions. Addressing these challenges requires improved data augmentation techniques, transfer learning methodologies, and optimization of ML architectures for real-time deployment in large-scale 5G networks.

5.3 Practical Implications

The findings of this study highlight the practical feasibility of ML-based approaches in optimizing real-world 5G networks. The deployment of Boosted Trees and Neural Networks in adaptive resource management systems can significantly enhance Quality of Service (QoS) metrics, minimizing latency and congestion fluctuations. Furthermore, SOM-based clustering techniques can assist in dynamic spectrum allocation, enabling autonomous network adaptation to traffic variations. Future research should focus on integrating hybrid AI-driven frameworks, incorporating reinforcement learning and federated learning paradigms to ensure scalable, efficient, and secure 5G network management

6. Conclusion

This study conducted a comprehensive evaluation of machine learning models for 5G resource allocation and network optimization, identifying Boosted Trees, Neural Networks (Levenberg-Marquardt), and Gaussian SVM as the top performing classification models due to their high accuracy, adaptability, and ability to handle dynamic traffic variations. Regression-based approaches, particularly Gradient Boosting and Polynomial Regression, demonstrated strong predictive capabilities in forecasting bandwidth fluctuations and latency trends. The results emphasize the synergistic potential of combining classification and regression techniques, enabling enhanced predictive modeling for real-time 5G optimization. The integration of Self-Organizing Maps (SOMs) for clustering-based resource segmentation further reinforces the importance of hybrid learning strategies in improving network efficiency and adaptive resource management. Future research should focus on developing hybrid ML architectures that integrate Deep Learning with Reinforcement Learning, enabling autonomous, self-optimizing 5G networks. The incorporation of Explainable AI (XAI) techniques is also critical for enhancing model interpretability, ensuring transparent and accountable decision-making in AI-driven 5G infrastructure. Additionally, federated learning approaches should be explored to enable distributed, privacy-preserving network intelligence, facilitating scalable and adaptive 5G deployments. As 6G networks emerge, further advancements in AI-driven spectrum allocation, energy-efficient resource optimization, and security-aware ML frameworks will be essential to ensure seamless, intelligent, and future ready wireless communication systems.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Author contributions:** The authors declare that they have equal right on this paper.

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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