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ABSTRACT

This report presents a comparative analysis of different machine learning models for efficient resource allocation in 5G networks. The exponential growth of data traffic and diverse user demands necessitate dynamic and optimized resource allocation to ensure high ***Quality of Service*** *(QoS) and network efficiency. We explore and compare the performance of various machine learning algorithms, including regression algorithms and Neural Networks in their ability to manage network resource like bandwidth. We evaluate each model based on key metrics like Mean Square Error and R-Squared. The report highlights the strengths and limitations of each approach, providing insights into the most suitable model for specific 5G network scenarios. Finally, we discuss future research directions and potential applications of machine learning in optimizing resource allocation for next generation networks.*

CHAPTER -1

INTRODUCTION

The ever-expanding digital landscape, fueled by the explosion of data traffic and diverse user demands, presents a formidable challenge for 5G networks. Ensuring high Quality of Service (QoS) and optimal network efficiency hinges on the ability to dynamically and effectively allocate resources like bandwidth. Traditional methods, often static and inflexible, struggle to adapt to this dynamic environment, leading to inefficiencies and compromised performance. In this context, machine learning (ML) emerges as a powerful tool, promising to revolutionize resource allocation in 5G networks.

This research dives into a comparative analysis of various Machine Learning algorithms, exploring their potential in optimizing bandwidth allocation within 5G networks. We move beyond the limitations of traditional methods by harnessing the data-driven insights and adaptive capabilities of Machine Learning models. Our investigation focuses on prominent categories like regression algorithms,neural networks and few more. Each model is evaluated based on key performance metrics like Mean Square Error (MSE) and R-Squared, providing a comprehensive understanding of their strengths and weaknesses.

By dissecting the performance of each algorithm, we aim to identify the most suitable model for specific 5G network scenarios.We conclude by exploring promising avenues for further investigation, venturing into the potential applications of ML for optimizing resource allocation in next-generation networks.

CHAPTER -2

2.1 PROBLEM STATEMENT

“With the exponential surge in data traffic and diverse user demands in 5G networks, how can we leverage machine learning to optimize resource allocation, like bandwidth, to ensure high Quality of Service (QoS) and network efficiency.”

2.2 PROBLEM DEFINITION

With the exponential surge in data traffic and diverse user demands in 5G networks, how can we leverage machine learning to optimize resource allocation, like bandwidth, to ensure high Quality of Service (QoS) and network efficiency. This research aims to compare and evaluate the performance of various machine learning models, including regression algorithms and neural networks, in dynamically allocating bandwidth within 5G networks, identifying the most suitable model for specific scenarios based on key metrics like Mean Square Error and R-Squared.

2.3 OBJECTIVE

The research aims to implement machine learning for dynamic bandwidth allocation in 5G networks, optimizing resource usage in response to changing demands. The primary objectives include ensuring high Quality of Service, enhancing network efficiency, and conducting a comparative analysis of regression models and neural networks. By prioritizing adaptability to real-time conditions, the research contributes insights for designing intelligent bandwidth allocation strategies in 5G networks.

CHAPTER -3

LITERATURE REVIEW

Paper 1 : An Optimal Wireless Resource Allocation of Machine-Type Communications in the 5G Network for Situation Awareness of Active Distribution Network

In this paper, an optimal wireless resource allocation scheme based on the 5G network is proposed, which can optimally support collaborative scheduling and resource allocation for normal sampling data and emergency sampling data. The exhaustive simulation and experimental results show that with limited resource blocks, our proposed algorithm can maintain the dropping ratio of lower data packets while achieving optimal energy efficiency for massive smart meters, comparing with other typical counterparts.

Paper 2 : A Social-Aware Resource Allocation for 5G Device-to-Device Multicast Communication

This paper tackles the issue of ineffective content sharing in 5G networks due to solely relying on physical factors for device-to-device connections. Their novel approach bridges this gap by considering both physical constraints and social aspects like shared interests to create efficient D2D multicast links. This not only boosts overall network throughput but also ensures fair channel allocation among different user groups, ultimately leading to a smarter and more satisfying content sharing experience for everyone

Paper 3 : Improved Resource Allocation in 5G MTC Networks

This paper proposes a resource allocation scheme with dynamic priorities for MTC devices with multiple radio access technologies (RATs). The proposed resource allocation scheme has two main parts namely medium access and resource allocation. The medium access leverages the broadcast nature of wireless signal and MTC devices' wait time to assign priorities using capillary band in a secure and integral way. At resource allocation, SNR, total induced transmission delay, and transmission-awaiting MTC devices are used to assign resources in the cellular band. The rumination of two-staged dynamic priorities in the proposed scheduling scheme brings significant performance improvements in outage and success probabilities. Compared to SNR-based schemes, the proposed mechanism performs well by expressively improving the outage and success probability by 20% and 30%, respectively.

Paper 4: Resource Allocation for Network Slicing in Mobile Networks

This paper provides a survey of resource allocation for network slicing. We focus on two classes of existing solutions: (i) reservation-based approaches, which allocate resources on a reservation basis, and (ii) share-based approaches, which allocate resources based on static overall shares associated to individual slices. We identify the requirements that a slice-based resource allocation mechanism should satisfy, and evaluate the performance of both approaches against these requirements.

Paper 5 : A Survey on Resource Allocation in Vehicular Networks

Vehicular networks, an enabling technology for Intelligent Transportation System (ITS), smart cities, and autonomous driving, can deliver numerous on-board data services. In this paper, we present a comprehensive survey on resource allocation schemes for the two dominant vehicular network technologies, e.g. Dedicated Short Range Communications (DSRC) and cellular based vehicular networks. We discuss the challenges and opportunities for resource allocations in modern vehicular networks and outline a number of promising future research directions.

CHAPTER - 4

PROJECT DESCRIPTION

This project dives into the potential of machine learning (ML) to revolutionize bandwidth management in 5G networks.. A comparative analysis of prominent models, including regression algorithms and neural networks, evaluates their potential to optimize resource allocation while ensuring high Quality of Service and network efficiency. Employing key metrics like Mean Square Error and R-Squared, this study identifies the most suitable models for specific scenarios.

This project aims to move beyond the limitations of static resource allocation and leverage ML's data-driven insights to unlock the full potential of 5G networks. Our research will contribute to the development of efficient and intelligent resource management strategies, ultimately enhancing user experience.

CHAPTER -5

REQUIREMENTS

<u>The major software requirements are</u>

1. Python

2. Python Libraries :

- **Numpy**
- **Pandas**
- **Matplotlib**
- **plotly**
- **Scikit- Learn**
- **Tensorflow**

3.IDE :

- **Google Colab**
- **VS Code**

CHAPTER - 6

METHODOLOGY

Data Acquisition and Preprocessing:

1. **Dataset Download :** A relevant dataset (400 rows) from Nokia containing features related to 5G network resource allocation, such as signal strength, required bandwidth, latency, and allocated resources.
2. **Data Augmentation :** To increase data size and potentially improve model performance, create a new dataset (800 rows) by applying data augmentation techniques suitable for the specific features.
3. **Feature Engineering :**
    a. ***Case 1***: Combine signal strength and required bandwidth into a single feature and resource allocation as another separate feature.
    b. ***Case 2***: Combine latency and latency signal interaction into a single feature and resource allocation as another separate feature.
4. **Data Split :** Divide each dataset (400 rows and 800 rows) into training, validation, and test sets using a consistent split ratio (e.g., 70/20/10).

Model Training and Evaluation :

5. **Model Selection :** Implement and train various machine learning models on each dataset and case combination:
    a. Linear Regression
    b. Polynomial Regression
    c. Decision Tree
    d. Random Forest
    e. Gradient Boosting Regressor
    f. Support Vector Machine
    g. KNN
    h. Neural Networks with different epochs(100, 200, 300)
6. **Evaluation Metrics :** Use appropriate metrics to evaluate the performance of each model, including:
    a. Mean Squared Error (MSE) to measure the average squared difference between predicted and actual resource allocation.
    b. R-Squared to measure the proportion of variance in the actual resource allocation explained by the model.

CHAPTER -7

EXPERIMENTATION

<u>Flow Chart</u>:

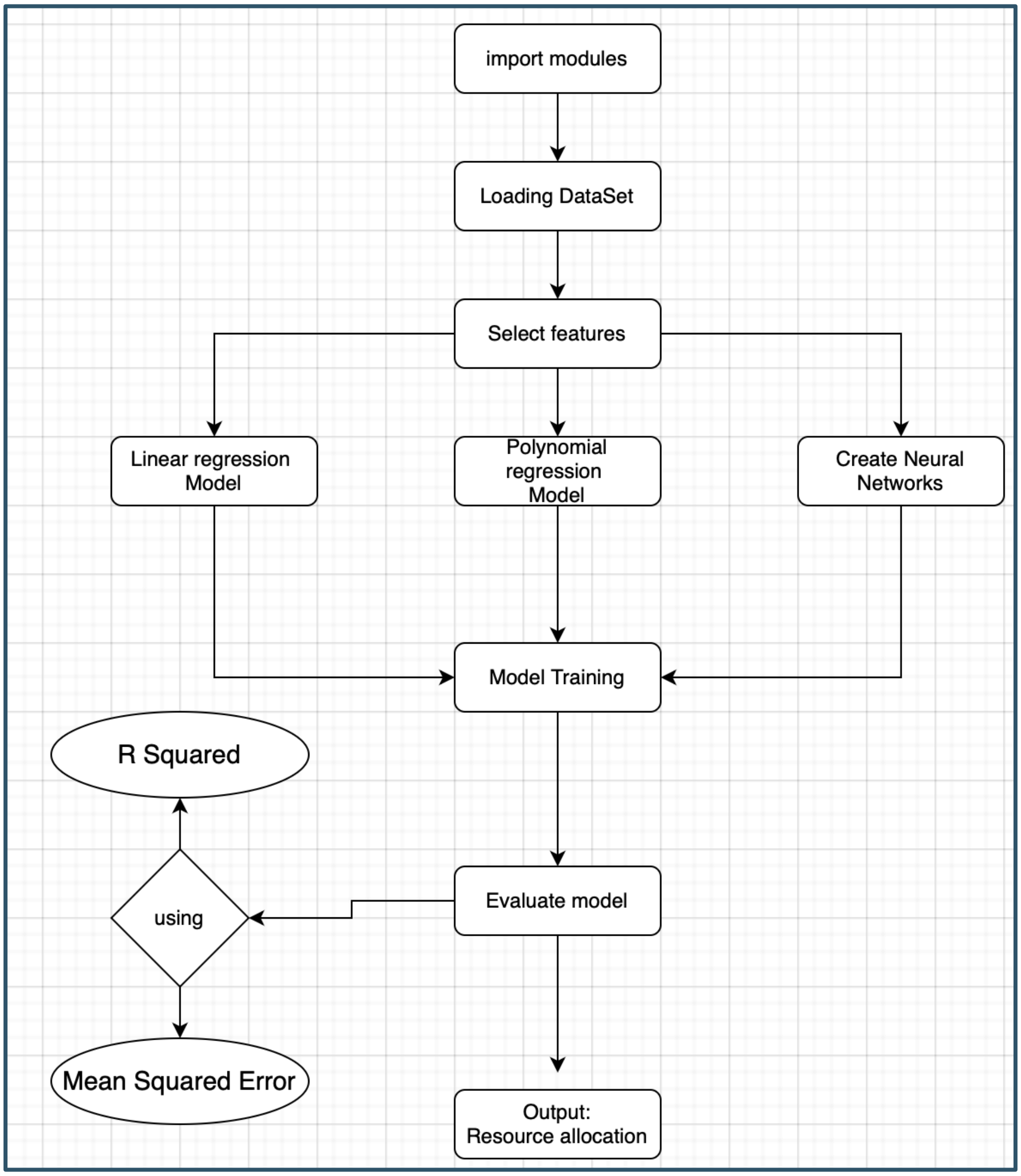


Figure 1

CHAPTER - 8

TESTING AND RESULTS

Testing :

Dataset - 400 Rows

Models	MSE	R-Squared
Linear Regression	0.007977063586	0.08959552499
Polynomial Regression	0.002299308514	0.7375850477
Decision Tree	0.004703125	0.4632428336
Random Forest	0.002055128687	0.7654527468
Gradient Boosting Regressor	0.0023825888	0.7280804543
Support Vector Machine	0.00637265417	0.2727031931
KNN	0.00412375	0.5293656101
Neural Network(100 epochs)	0.002371098403	0.7293918277
Neural Network(200 epochs)	0.002256420455	0.7424797661
Neural Network(300 epochs)	0.001546427125	0.8235097214

Features : SignalStrength,ReqBandwidth,ResAlloc (Table 1)

Models	MSE	R-Squared
Linear Regression	0.006822902316	0.2213173764
Polynomial Regression	0.005233160599	0.4027510529
Decision Tree	0.0075625	0.1369087424
Random Forest	0.004798681489	0.4523371847
Gradient Boosting Regressor	0.004263375708	0.5134304395
Support Vector Machine	0.007305186967	0.1662753049
KNN	0.00595375	0.3205117917
Neural Network(100 epochs)	0.004656860046	0.4685229496
Neural Network(200 epochs)	0.003443699724	0.6069782313
Neural Network(300 epochs)	0.003807771971	0.5654274778

Features : Latency,LatencySignalInteraction,ResAlloc(Table 2)

Dataset - 800 Rows

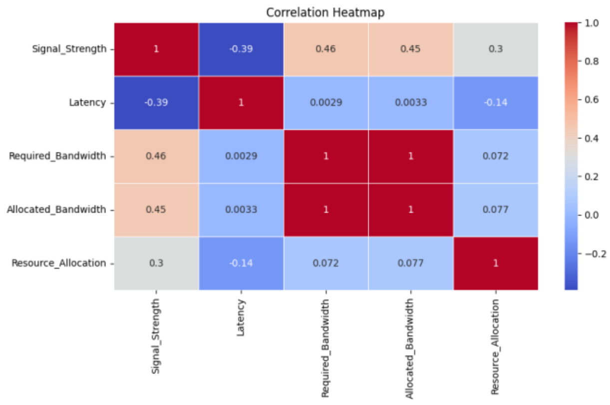
Models	MSE	R-Squared
Linear Regression	0.008350934415	0.01463900711
Polynomial Regression	0.006991935639	0.1749928449
Decision Tree	0.01256163194	-0.4821984595
Random Forest	0.007440360124	0.1220814013
Gradient Boosting Regressor	0.007094840345	0.1628506967
Support Vector Machine	0.007865193122	0.07195361391
KNN	0.008439375	0.004203539823
Neural Network(100 epochs)	0.007102016543	0.1620039477
Neural Network(200 epochs)	0.006901916765	0.185614541
Neural Network(300 epochs)	0.007604512753	0.1027123595

Features : SignalStrength,ReqBandwidth,ResAlloc(Table 3)

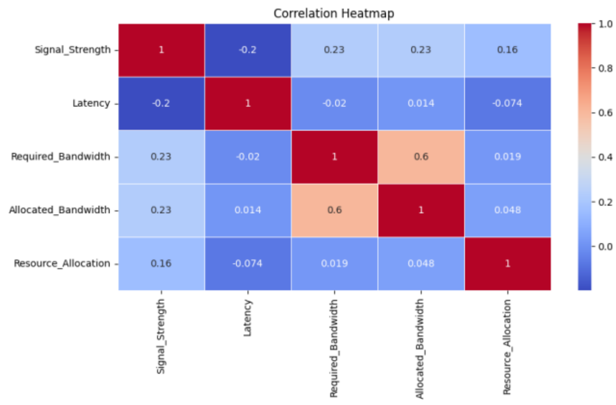
Models	MSE	R-Squared
Linear Regression	0.00781602176	0.07775554451
Polynomial Regression	0.007914167807	0.06617489003
Decision Tree	0.01328766539	-0.567866123
Random Forest	0.009719926536	-0.1468939865
Gradient Boosting Regressor	0.008453770128	0.0025049997
Support Vector Machine	0.0079872464	0.0575520472
KNN	0.009686875	-0.1429941003
Neural Network(100 epochs)	0.007437869324	0.122375301
Neural Network(200 epochs)	0.007382464965	0.1289126885
Neural Network(300 epochs)	0.007402349873	0.1265663866

Features : Latency,LatencySignalInteraction,ResAlloc(Table 4)

Result :



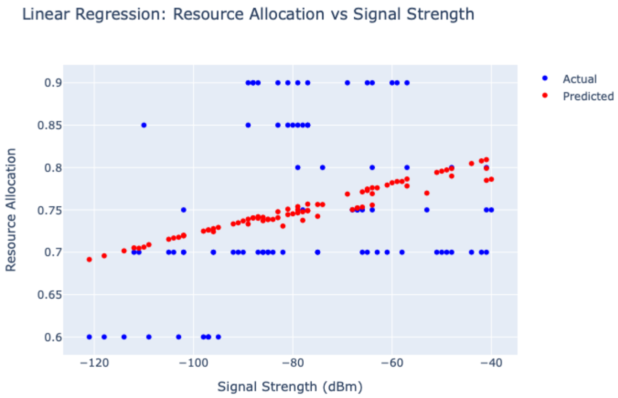
400 Rows-Figure 2

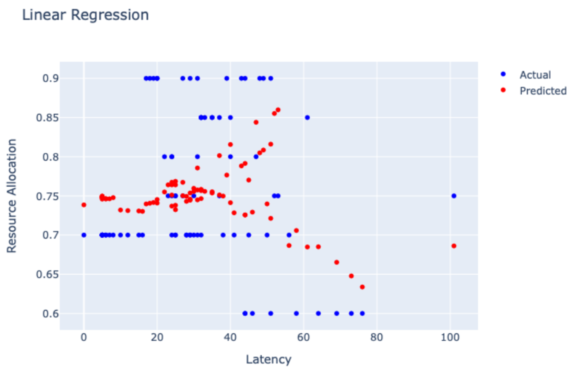


800 Rows-Figure 3

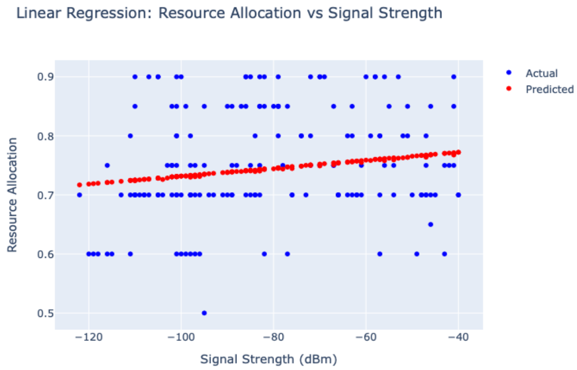
- ## Linear Regression :

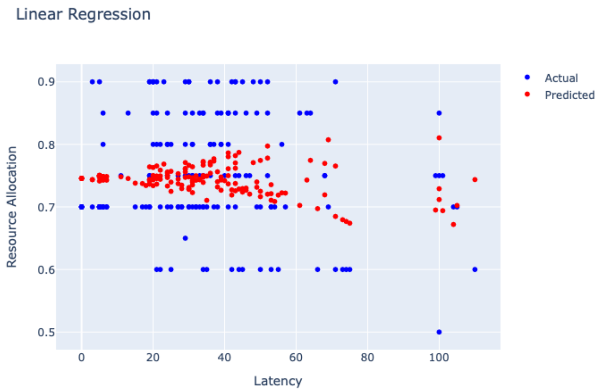
Dataset-400 Rows





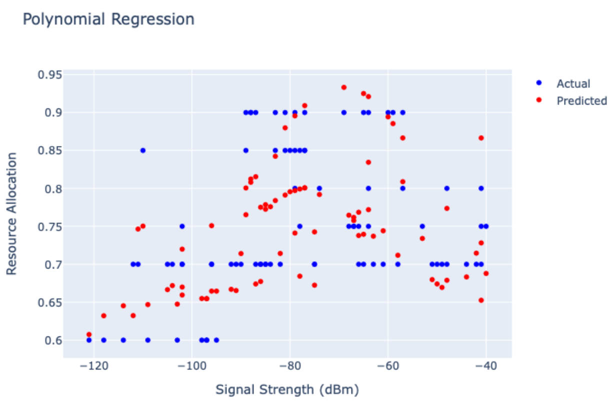
Dataset-800 Rows



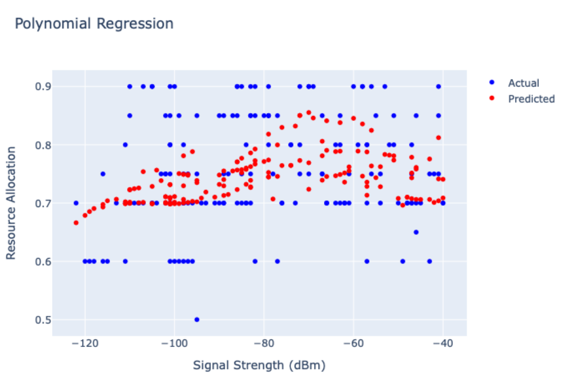


- **<u>Polynomial Regression</u> :**

Dataset-400 Rows

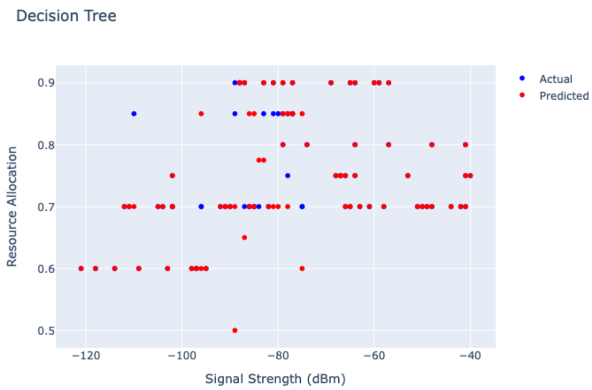


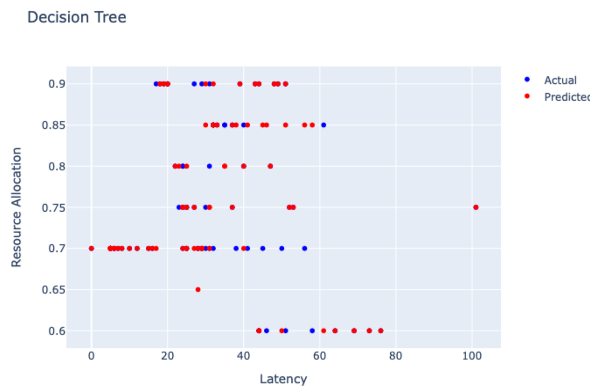
Dataset-800 Rows



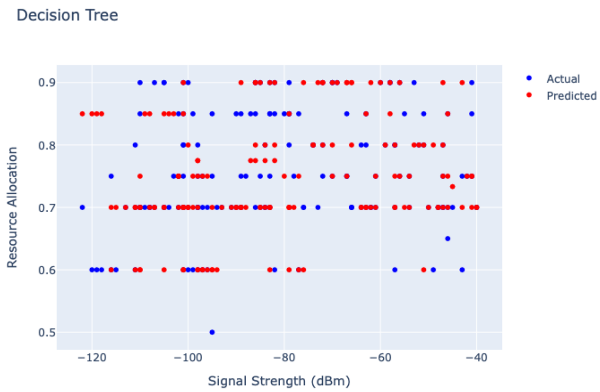
- **Decision Tree :**

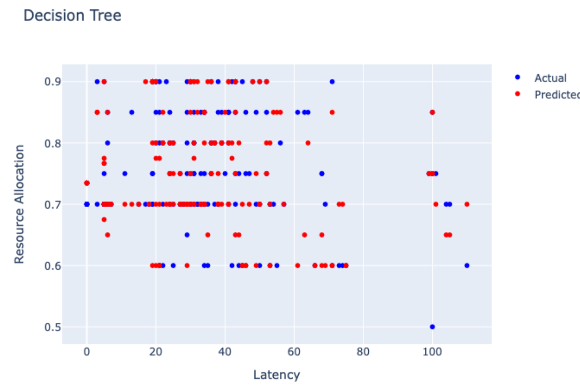
Dataset-400 Rows





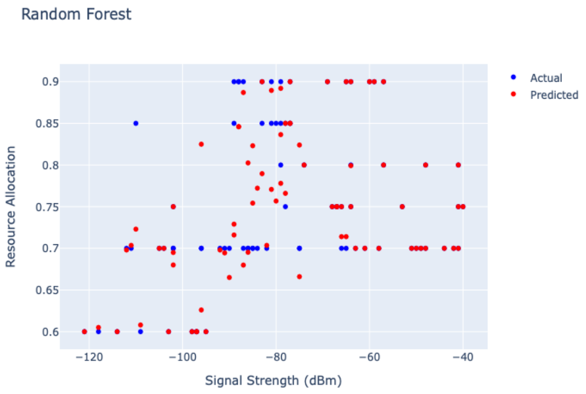
Dataset-800 Rows

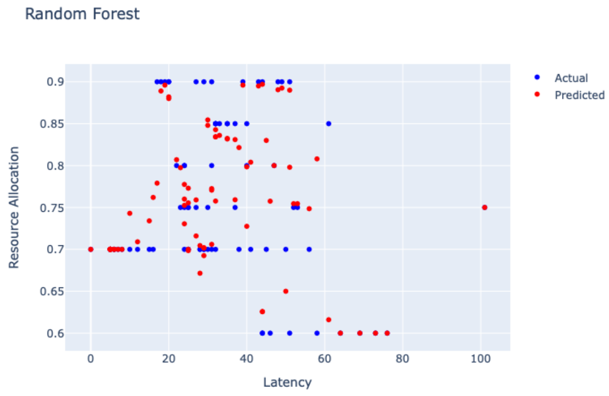




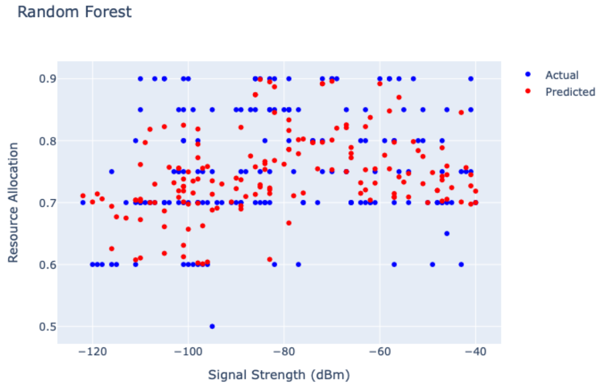
- **<u>Random Forest</u>** :

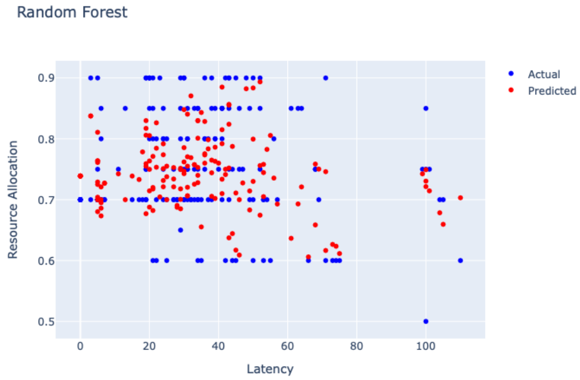
Dataset-400 Rows





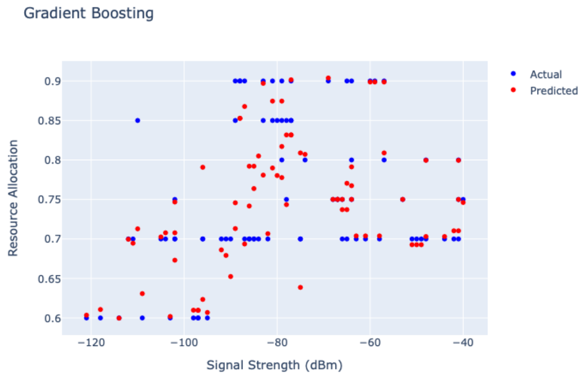
Dataset-800 Rows

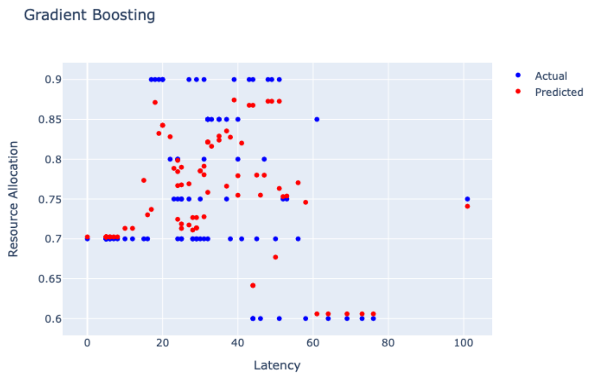




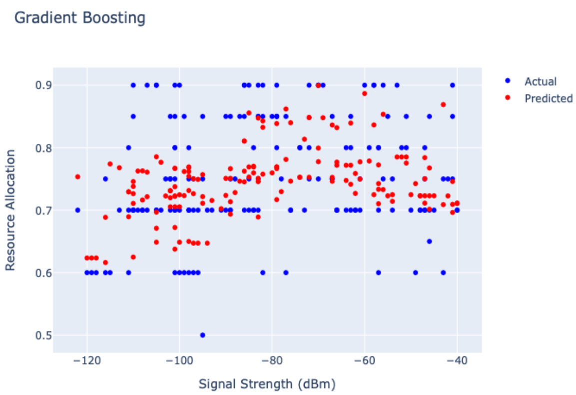
- **<u>Gradient Boosting Regressor</u> :**

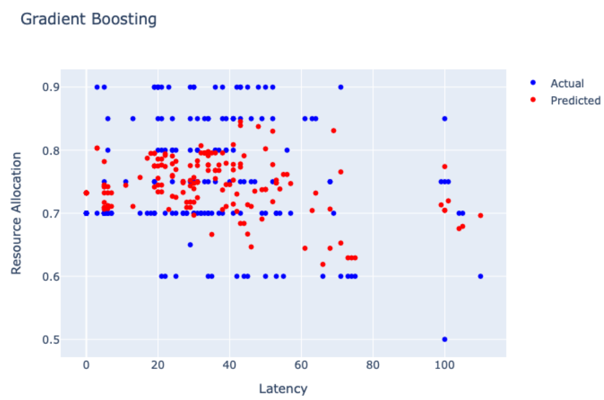
Dataset-400 Rows





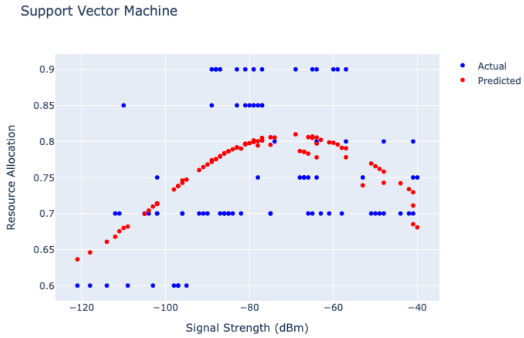
Dataset-800 Rows

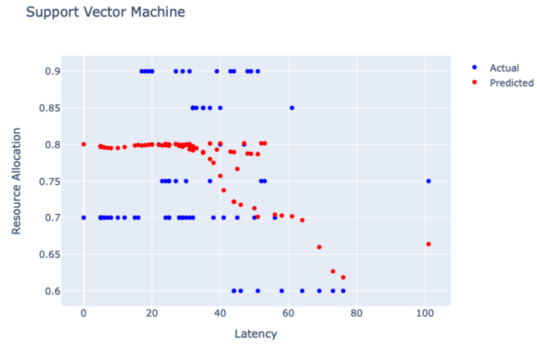




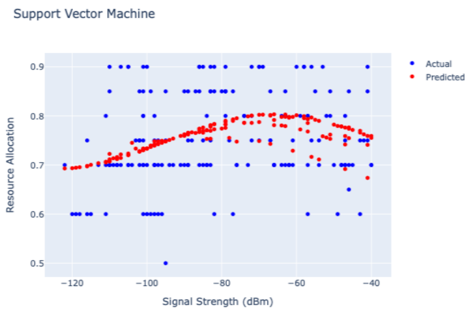
- **<u>Support Vector Machine</u>:**

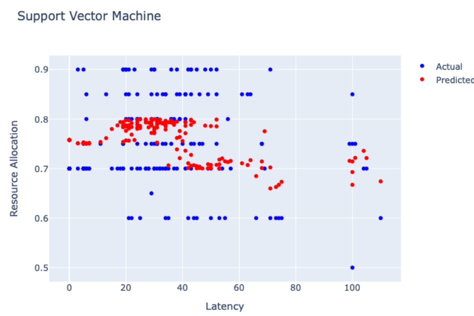
Dataset-400 Rows





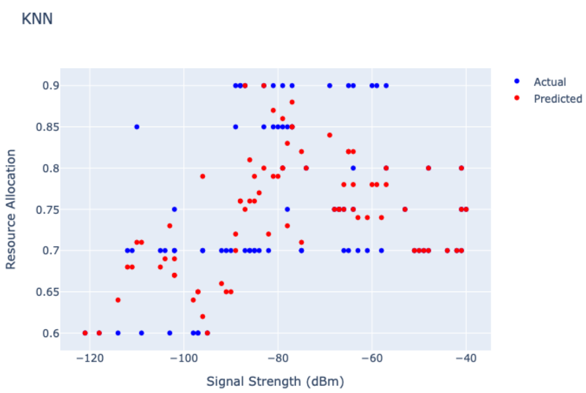
Dataset-800 Rows



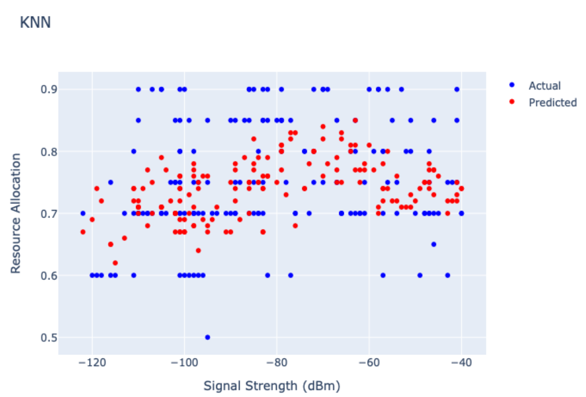


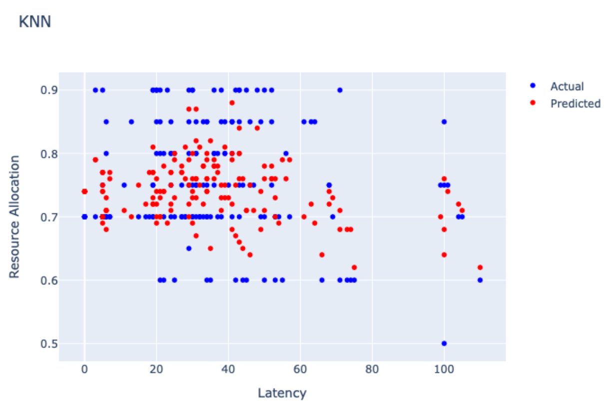
- **KNN :**

Dataset-400 Rows



Dataset-800 Rows





CONCLUSION

The table in the **Testing** shows the Mean Squared Error (MSE) and R-Squared values for different machine learning models trained on different datasets. There are two datasets : one with 400 rows of data and another with 800 rows of data and in the features we used [SignalStrength, ReqBandwidth, ResourceAllocation] and[Latency,LatencySignalinteraction,ResourceAllocation].

Overall, the models trained on the larger datasets (800 rows) tend to have higher MSE and lower R-Squared values than the models trained on the smaller datasets (400 rows). This suggests that the larger datasets may be more difficult to learn from, or that the models may be overfitting to the training data.

Here are some of the specific findings:

- For the models trained on the 400-row dataset, Random Forest and Neural Network (300 epochs) have the lowest MSE and highest R-Squared values, suggesting that they are the best performing models on this dataset.
- For the models trained on the 800-row dataset, Gradient Boosting Regressor and Neural Network (200 epochs) have the lowest MSE and highest R-Squared values, suggesting that they are the best performing models on this dataset.
- It is interesting to note that the performance of the Neural Network models generally improves as the number of epochs increases, while the performance of the other models does not. This suggests that the Neural Networks may be more prone to overfitting, and that it is important to carefully choose the number of epochs to train them for.

In conclusion, the size of the dataset and the features used can have a significant impact on the performance of machine learning models. It is important to experiment with different models and features to find the best combination for a particular task.

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Resource Allocation in 5G Platoon Communication: Modeling, Analysis and Optimization

Kaggle – www.kaggle.com

Youtube – www.youtube.com