Unsupervised Machine Learning Approaches for Analyzing 5G Quality of Service

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Abstract
Particular emphasis on K-Means, Agglomerative Clustering, DBSCAN, and Hierarchical Clustering, this research studies the analysis of 5G Quality of Service (QoS) using unsupervised machine learning models. Using these clustering techniques, our objective is to classify various quality of service (QoS) parameters, such as throughput, latency, and jitter, and assess the performance of these parameters by employing metrics such as the Silhouette Score, Davies-Bouldin Index, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Standard Root Mean Squared Error (SRMSE). While K-Means, Agglomerative, and Hierarchical Clustering all perform similarly, attaining strong cluster separation and low prediction errors, DBSCAN excels in finding dense clusters but shows larger errors. The results suggest that all three clustering methods are comparable in their performance. This research emphasizes the benefits and limits of each clustering approach, offering useful insights that can be used to optimize the performance of 5G networks and ensure that high-quality service is delivered. Furthermore, our results highlight the significance of adopting proper clustering approaches in order to improve quality of service in 5G networks.

Keywords: **5G, Quality of Service, Machine Learning, K-Means Clustering, Principal Component Analysis, Network Optimization**

Introduction

The introduction of 5G technology ushers in a new era in the field of telecommunications, bringing with it the promise of data transfer rates that have never been seen before, ultra-low latency, and the ability to link a large number of devices all at once. This significant advancement is anticipated to bring about a revolution in a variety of sectors, including healthcare, automotive, and smart cities, by making it possible to develop novel applications and services. However, as the complexity of 5G networks and the demand for them continue to grow, it is becoming more important to guarantee and maintain the highest possible Quality of Service (QoS). Quality of service (QoS) comprises a variety of performance characteristics, including throughput, latency, jitter, and dependability, all of which are necessary for the delivery of communication services that are both smooth and efficient. For the purpose of improving both the user experience and the performance of the network, it is essential to analyze and optimize these parameters.

Models that use machine learning (ML), in particular those that use unsupervised learning approaches, provide strong tools that may be used to analyze and improve quality of service in 5G networks. Because it does not need labeled data, unsupervised learning is an excellent method for discovering hidden patterns and structures within huge datasets. This is in contrast to supervised learning, which requires labeled data. As a subset of unsupervised learning, clustering algorithms are especially helpful for this purpose since they group data points based on their similarities, therefore discovering different patterns and anomalies in network performance. This makes clustering algorithms highly suitable for this purpose. A total of four different clustering algorithms—K-Means, Agglomerative Clustering, DBSCAN, and Hierarchical Clustering—are

used in this investigation for the purpose of analyzing and improving the quality of service (QoS) of 5G networks.
K-Means clustering is a popular technique that divides data into k groups based on the similarity of their features. Through repeated refinement of the cluster centroids, the algorithm strives to minimize the variation that exists within each cluster. The fact that it is both simple to understand and efficient in terms of computing makes it a popular option for a wide range of applications. K-Means, on the other hand, makes the assumption that clusters are spherical and of comparable size, which may not necessarily be the case with data collected from the actual world.
A tree-like structure of nested clusters is constructed using a kind of hierarchical clustering known as agglomerative clustering. This structure is constructed by repeatedly merging or dividing clusters depending on a linking criteria that is selected. The fact that this approach does not presume any specific cluster form makes it more adaptable than the K-Means statistical technique. On the other hand, it requires a greater amount of processing effort, particularly when dealing with huge datasets, and it may be susceptible to noise and outliers.
An additional strong clustering technique is known as DBSCAN, which stands for density-based spatial clustering of applications with noise. This algorithm combines data points according to density, therefore detecting clusters that are of varied sizes and forms. In contrast to K-Means and Agglomerative Clustering, DBSCAN is able to properly manage noise and outliers, which makes it especially suitable for datasets that are both complicated and large. On the other hand, it is necessary to carefully tune its parameters (epsilon and minimum samples), and it may have difficulty dealing with clusters of differently dense populations.
Comparable to Agglomerative Clustering, Hierarchical Clustering is a method that creates a hierarchy of clusters. However, it may also be represented as a dendrogram, which offers a visual depiction of the clusters that are nested inside each other. This approach is both adaptable and user-friendly, making it possible to easily identify clusters at a variety of granularity levels. On the other hand, similar to Agglomerative Clustering, it is both computationally costly and susceptible to environmental noise.
Each of these four clustering methods is used in this research project in order to conduct an analysis of a 5G quality of service dataset. The performance of these algorithms is evaluated by using a variety of measures, including the Silhouette Score, Davies-Bouldin Index, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Standard Root Mean Squared Error (SRMSE). Through a comparison of various algorithms, our objective is to determine which approach is the most efficient in terms of classifying and optimizing quality of service metrics in 5G networks.
In terms of organization, the analysis is as follows: Before anything further, the dataset is preprocessed in order to deal with missing values, convert data that is not numeric, and standardize the features. The next step is to use Principal Component Analysis (PCA), which aims to minimize the dimensionality of the dataset in order to make visualization and grouping more straightforward. After that, every clustering method is applied to the standardized data, and the performance of each algorithm is assessed based on the metrics that were previously specified. A comparison of the findings is made in order to emphasize the advantages and disadvantages of each technique, hence offering insights into the appropriateness of each method for 5G quality of service study.

Literature Review

Tsipi, L. et al. (2022), Mass connectivity demands make terrestrial cellular communications networks struggle to serve coexisting users and devices. Additionally, natural calamities and unforeseen occurrences provide unpredictable data flow, producing network congestion. For handling increased data traffic and offloading terrestrial infrastructure, on-demand network entities like fixed or airborne base stations have been suggested. An unsupervised machine learning algorithm is used to put unmanned aerial vehicles (UAVs) at high-data-traffic areas in this paper's terrestrial network offloading strategy. Using the k-medoid method, the suggested technique groups impacted users. To maximize system offloading, a cluster selection strategy is used to pick UAVs depending on their quantity. Comparing the suggested technique to terrestrial picocellintegrated offloading solutions and other UAV-aided systems shows considerable offloading, throughput, spectrum efficiency, and sum rate increases under varied UAV numbers.

Lefoane, M. et al. (2022), IoT device deployment has grown exponentially. More IoT devices have been linked than non-IoT gadgets in recent years. IoT devices are increasingly essential to national infrastructure as their number grows. Hackers and cybercriminals target IoT devices because of their limitations. Botnet attacks are a major Internet danger. This paper suggests pattern-based feature selection for ML-based botnet detection. One technique uses the most dominating pattern feature values, while the other uses maximum frequent itemset mining. Gini impurity and unsupervised clustering are used to automatically choose the most influential characteristics. The evaluation findings demonstrate that the offered strategies increased detection system performance. For top models, the method has 100% true positives and 0% false positives. The suggested solutions minimize computing cost, as shown by system detection speed.

Kaur, J. wireless communication systems are vital for entertainment, business, commercial, health, and safety applications in contemporary civilization (2021). These technologies keep developing, and 5G wireless networks are being deployed worldwide. Researchers and industry leaders are already considering 6G wireless technologies. AI and ML will be crucial to 6G wireless networks. All wireless system components and building blocks up to 5G, such as physical, network, and application layers, will use AI/ML. This overview paper covers cutting-edge wireless system ideas like 6G and ML's involvement in them. We demonstrate the application and function of ML approaches in each tier of a 6G conceptual model. In wireless communication systems, we examine traditional and modern ML approaches such supervised and unsupervised learning, Reinforcement Learning (RL), Deep Learning (DL), and Federated Learning (FL). Finally, we discuss 6G network ML and AI applications and research problems.

O. Aouedi. et al. (2022), Smart devices have increased data creation and heterogeneity, necessitating new network solutions for traffic analysis. To automatically process massive data sets, these systems must be clever and scalable. High-performance computing (HPC) makes machine learning (ML) easy to use to tackle complicated problems, and its efficacy has been shown in healthcare and computer vision. Meanwhile, network slicing (NS) has garnered interest from business and research due to its importance in meeting diverse service needs. Thus, ML use in NS management is intriguing. We analyzed network data to define network slices based on traffic flow trends in this article. Feature selection was used to choose 15 of 87 relevant features from a dataset of over 3 million occurrences for dimensionality reduction. K-means clustering is then used to comprehend and identify traffic behaviors. A good association was found among unsupervised learning cases in the same cluster. This technique may be implemented in real life utilizing network function virtualization.

S. Sevgican. 5G cellular networks have many new features compared to legacy networks, such as network data analytics function (NWDAF), which allows network operators to implement their own machine learning (ML)-based data analytics methodologies or integrate third-party solutions. This article describes NWDAF's structure and protocols as stated in 3GPP standard papers. A cell-based synthetic data set for 5G networks based on 3GPP fields is then created. Anomalies (e.g., rapidly increased cell traffic) are added to this data collection and characterized by cell, subscriber type, and user equipment. Three ML models—linear regression, long-short term memory, and recursive neural networks—are then used to evaluate NWDAF's behavior information estimation (e.g., network traffic anomalies) and network load prediction. Three models minimize the mean absolute error, computed by subtracting the actual produced data from the model forecast value, for network load prediction. ML models logistic regression and extreme gradient boosting improve the area under the receiver operating characteristic curve to classify anomalies. Network load prediction is better using neural network methods than linear regression, and anomaly detection is better with tree-based gradient boosting. These estimates should improve 5G network performance using NWDAF.

M. E. et al. (2019), Driven by the need to handle expanding mobile traffic, 5G is planned to be a major enabler and leading infrastructure provider in the ICT sector by enabling a range of future services with various needs. Machine learning (ML) is expected to help realize the 5G vision due to the network's growing complexity and new use cases like autonomous cars, industrial automation, virtual reality, e-health, and intelligent applications. This article examines ML-based 5G solutions. First, we define supervised, unsupervised, and reinforcement learning and examine the use of ML in mobile and wireless communication, grouping the literature by learning type. We then describe possible ways ML might assist each target 5G network need, stressing its individual use cases and assessing their effect and constraints on network operation. Finally, this study examines Beyond 5G (B5G) characteristics and suggests how ML might help realize B5G. This article encourages debate on how ML might help deliver autonomous 5G/B5G mobile and wireless communications.

M. Z. Asghar. We provide an auto-encoder-based machine learning framework for self-organizing networks (SON) in this research. Traditional machine learning methods like K Nearest Neighbor cannot forecast accurately. Since they need a batch of data to train on, they cannot be extended for sequential data. We provide a framework for artificial neural network-based techniques like autoencoders (AE). The suggested framework outperforms existing machine learning techniques in accuracy and extensibility. The research evaluates autoencoders (AE) for cell outage detection. First, we quickly present deep learning (DL) and explain why it is promising for making self-organizing networks intelligent, cognitive, and intuitive so they act as completely self-configured, self-optimized, and self-healed cellular networks. SON is described using intrusion detection and mobility load balancing. Our empirical research proposes an autoencoder-based cell outage detection system utilizing SON simulator data. Finally, we compare the proposed framework to existing frameworks.

Abidi, M.H. Network slicing splits the physical network into several logical networks to provide upcoming applications with higher performance and flexibility (et al., 2021). These apps have created massive data counts on many mobile phones. This has created significant issues and affected network slicing performance. A mixed learning approach is used to build efficient network slicing. Our approach includes data gathering, optimal weighted feature extraction (OWFE), and slicing classification. The 5G network slicing dataset includes attributes like “user device type, duration, packet loss ratio, packet delay budget, bandwidth, delay rate, speed, jitter, and modulation type.” We then performed the OWFE, which multiplies attribute values by a weight function to have high scale variation. We hybridized glowworm swarm optimization with deer hunting optimization algorithm (DHOA) to optimize this weight function and dubbed the model glowworm swarm-based DHOA. We categorized each device's network slices such “eMBB, mMTC, and URLLC” using a hybrid classifier employing deep belief and neural networks for the specified properties. GS-DHOA optimizes both networks' weight functions. The experiment showed that the suggested approach might affect 5G network slicing.

Usama, M. Machine learning and artificial intelligence have long been employed in networking research, although much of it has focused on supervised learning. Unsupervised machine learning utilizing unstructured raw network data to enhance network performance and deliver services like traffic engineering, anomaly detection, Internet traffic categorization, and quality of service optimization is becoming more popular. Due to its success in computer vision, natural language processing, voice recognition, and optimal control (e.g., for autonomous self-driving automobiles), unsupervised learning approaches are gaining popularity in networking. Unsupervised learning also eliminates the requirement for labeled data and human feature building, making machine learning flexible, broad, and automatic. This survey article covers networking unsupervised learning applications. We give a detailed assessment of current unsupervised learning advances and their applications in networking learning challenges. Future paths and open research concerns are discussed, along with possible hazards. Several survey articles on machine learning in networking have been published, but none have been as comprehensive. We hope to increase knowledge by carefully combining lessons from past survey publications and covering new breakthroughs and innovations in this timely study.

Zhu, G. According to et al. (2019), 5G networks provide ubiquitous connection, very low latency, and high-speed data transmission. Over 5G networks, machine type communication (MTC), enhanced mobile broad band (eMBB), and ultra-reliable low latency communications (URLLC) must meet distinct QoS standards. Softwarization, slicing, and network capability exposing of 5G provide dynamic programming for QoS guarantee, unlike the prior "one size fits all" solution. With the increasing complexity and dynamics of network behaviors, it is difficult for a programmer to develop traditional software codes to schedule network resources based on expert knowledge, especially when network events and QoS anomalies are not quantitatively related. Machine learning allows computers to learn from data and enhance task performance and decision-making without being explicitly programmed. Machine learning and communication technologies are merging. A supervised learning-based 5G QoS assurance architecture was suggested in this study. Supervised machine learning can adapt to changing network conditions. They can learn from previously provided QoS data and abnormalities and automatically and properly rebuild the connection between the two. They may then do automated mitigation or provide advice. High-confidence supervised machine learning algorithms may forecast future QoS abnormalities. This research presents a decision tree-based QoS anomaly root cause tracking case study to evaluate the framework design.

ΜΠΑΡΤΣΙΩΚΑΣ, I. This survey (2023) examines the application of machine learning (ML) methods for resource management in 5G/B5G wireless cellular networks. The radio resource management (RRM) problem is multi-constraint due to increasing user requirements, diverse performance metrics, and novel technologies like millimeter wave transmission, massive multiple-inputmultiple-output configurations, and non-orthogonal multiple access. Since they reduce the computational cost of RMM, ML and mobile edge computing (MEC) may enhance end-user QoS. A state-of-the-art examination of ML-based RRM algorithms, grouped by learning type, prospective applications, and MEC implementations, is provided to determine the best solutions for different RRM sub-problems. We use and evaluate ML techniques for throughput prediction as an indicative RRM job to highlight the possibilities and efficiency of ML-based systems. We classify or regress the issue using the appropriate metrics. Finally, AI/ML RRM difficulties, constraints, and limits for 5G and B5G networks are detailed.

Tsipi, L. The ever-changing environment of wireless communication systems, including fifth-generation (5G) networks and beyond (B5G), requires accurate Modulation and Coding Scheme (MCS) prediction to optimize data transmission efficiency and quality of service. Traditional MCS selection approaches use predetermined rules and heuristics for transparency and control but not adaptation to changing wireless environments. Machine Learning (ML) has revolutionized MCS prediction. ML promises better accuracy and flexibility in dynamic wireless situations using data-driven models. This work is the first to investigate and assess machine learning (ML) methods for predicting MCS in orthogonal frequency-division multiplexing (OFDM) systems. It also presents a Deep Neural Network (DNN) architecture with two hidden layers for MCS prediction, guided by accuracy, precision, recall, and F1-score. ANN, SVM, RF, and Bagging with k-NN are explored ML approaches. With a dataset from non-standalone 5G network simulations, these approaches are trained and evaluated. The research characterizes the environment using physical layer measurements and a ray-tracing route loss prediction model. Advanced data mining methods preprocess raw data to reduce model underfitting and overfitting. RF and B-kNN algorithms have the lowest accuracy, below 88.65%, while the ANN with two hidden layers has the best accuracy, 98.71%. SVM and ANN models with one and four hidden layers predict MCS with 97.02 to 97.30% accuracy.

Kamel, M.B. With the advent of 5G technology, congestion management is a crucial issue for effective communication. Several 5G congestion management algorithms have been suggested to regulate and anticipate congestion. However, choosing the best congestion control model is crucial yet difficult. In this study, we compare supervised and unsupervised machine learning methods for forecasting 5G congestion nodes. Measuring prediction consistency was difficult due to the data set columns' high volatility. We examined twenty-six supervised and seven clustering techniques. Finally, we selected the top five algorithms based on performance.

Yuliana, H. Wireless communication is quicker and more dependable with 5G (2024). Coverage prediction helps 5G network operators optimize infrastructure development and offer high-quality services. A detailed examination of machine learning techniques for 5G coverage prediction focuses on dominating feature parameters and accuracy. Top performers include the Random Forest algorithm with an RMSE of 1.14 dB, MAE of 0.12, and R2 of 0.97. CNN, the best deep learning system, predicts 5G coverage with an RMSE of 0.289, MAE of 0.289, and R2 of 0.78. Random Forest models have 98.4% accuracy, precision, recall, and F1-score. CNN surpasses other deep learning models but behind Random Forest. The final Random Forest and CNN models outperform prior models, according to the study. The most important feature parameter for 5G coverage prediction across all methods is 2D Distance Tx Rx. Horizontal and vertical distances increase prediction outcomes beyond earlier investigations. The report advises using machine intelligence and deep learning methods in network building and optimization to forecast 5G coverage. In conclusion, the Random Forest method is best for 5G coverage prediction, however deep learning techniques, notably CNN, may be used for satellite image spatial data. These precise projections help network providers allocate resources efficiently, providing high-quality services in the constantly expanding 5G technological environment. A deep knowledge of coverage prediction is essential for 5G network design and service reliability.

R. Yadav (2018), This paper presents a recommendation system for e-commerce that utilizes client profiles to provide personalized product recommendations. The system uses data about the clients' preferences and previous purchases to generate recommendations.

V. Prakaulya (2017) The paper proposes a time series decomposition model for forecasting railway passenger numbers. The model decomposes the time series data into different components, such as trend and seasonality, and uses them to make predictions about future passenger numbers.

D. Bhuriya (2017) This paper explores the use of linear regression for predicting stock market trends. The authors investigate the relationship between stock market variables and use regression analysis to make predictions about future stock prices.

R. Verma (2017) The paper focuses on the use of neural networks for stock market prediction. The authors train neural networks using historical stock market data and use them to predict future stock prices.

Kewat (2017) The paper examines the application of support vector machines (SVMs) for forecasting financial time series. The authors train SVM models using historical financial data and evaluate their performance in predicting future values.

A. Sharma (2017) This paper provides a survey of different machine learning approaches used for stock market prediction. The authors review various techniques, including regression, neural networks, and support vector machines, and discuss their effectiveness in predicting stock prices**.**

S. Sable (2017) The paper proposes the use of genetic algorithms and evolution strategies for stock price prediction. The authors employ these optimization techniques to optimize the parameters of a prediction model and improve its accuracy.

A. Roshan (2018) The paper presents a credit card fraud detection system based on decision tree technology. The authors utilize decision trees to classify credit card transactions as either fraudulent or legitimate based on various features and patterns.

H. Soni (2018) This paper explores the use of machine learning techniques to identify patients with rare diseases from electronic health records. The authors develop models that analyze patient data and make predictions about the likelihood of rare diseases

A. Saxena (2020) The paper proposes a glaucoma detection system based on convolutional neural networks (CNNs). The authors train CNN models using eye images and use them to classify images as either normal or indicative of glaucoma.

B. Bamne (2020) The paper investigates the application of transfer learning and convolutional neural networks for object detection. The authors utilize pre-trained CNN models and adapt them for detecting objects in different contexts.

Gupta, P. (2022) The paper presents an AIoT-based device that enables real-time object recognition for visually impaired individuals. The system combines object recognition algorithms with voice conversion technology to provide auditory feedback to users.

A. Taiwade (2022) This paper proposes a hierarchical K-means clustering method for a friend recommendation system. The authors use clustering techniques to group users based on their profiles and recommend friends from within the same cluster.

R. Baghel (2022) The paper introduces a deep learning-based system for human face mask identification. The authors utilize deep learning algorithms and OpenCV techniques to detect and classify faces as either wearing or not wearing masks.

M. Ranjan (2022) The paper investigates the use of random forest and deep learning techniques for cancer prediction. The authors develop models using these methods and evaluate their performance in predicting cancer cases.

Singh, Upendra (2022) The paper presents a system for activity detection and people counting using the Mask-RCNN architecture combined with bidirectional ConvLSTM. The authors use this system to analyze video data and detect different activities and count the number of people involved .
Singh, Shani Pratap (2022) This paper proposes a multi-stage CNN architecture for face mask detection. The authors develop a system that can detect whether a person is wearing a face mask or not using deep learning techniques.
U. Singh (2022) The paper focuses on the analysis and detection of Monkeypox using the GoogLeNet model. The authors utilize the GoogLeNet model to classify images and identify cases of Monkeypox .

Proposed Methodology
3.1 Proposed flowchart

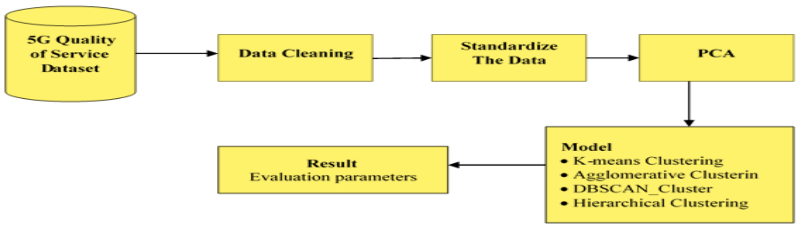

Figure 1. Comprehensive workflow for analyzing the Quality of Service (QoS) in 5G networks

The figure 1. illustrates a comprehensive workflow for analyzing the Quality of Service (QoS) in 5G networks using various machine learning clustering models. The process begins with the acquisition of a 5G Quality of Service dataset, which serves as the foundational input for the analysis.

3.2 Proposed Algorithm
3.2.1 Hierarchical Clustering

- **Load the Data:**
  - Import the dataset for analysis.
- **Clean the Data:**
  - Address any missing values.
  - Convert categorical or non-numeric columns to numeric format.
  - Remove columns that are not relevant to the analysis.
- **Standardize the Dataset:**
  - Normalize the data using StandardScaler to ensure uniformity.
- **Perform Dimensionality Reduction:**
  - Apply Principal Component Analysis (PCA) to reduce the number of dimensions in the data.
- **Identify Optimal Clusters:**
  - Use dendrograms to determine the ideal number of clusters for the dataset.
- **Conduct Hierarchical Clustering:**
  - Initialize AgglomerativeClustering with the determined number of clusters.
  - Merge clusters based on a specific linkage criterion.
- **Assess Clustering Performance:**
  - Evaluate the clustering results using metrics like the silhouette score and Davies-Bouldin index.
  - Compute additional metrics: MSE, RMSE, SRMSE, ARI, AMI, completeness score, homogeneity score, V-measure, Calinski-Harabasz index, and Fowlkes-Mallows index.
  - Measure classification performance with accuracy, precision, recall, and F1 score.

Implementation And Result
4.1 Hardware and software requirements: It is necessary to have a solid hardware and software infrastructure in order to analyze the Quality of Service (QoS) of 5G networks. This is because the analysis involves handling massive amounts of data and sophisticated calculations. When it comes to the hardware, it

is vital to have high-performance computing systems that are equipped with multi-core processors, a large amount of random access memory (ideally 32GB or more), and a substantial storage capacity (SSD for quicker data access). When it comes to software, it is essential to have powerful data analytics and machine learning frameworks, such as Python with libraries like Scikit-learn, Pandas, and TensorFlow, as well as visualization tools like Matplotlib and Seaborn. Furthermore, the use of distributed computing platforms such as Apache Spark has the potential to considerably boost data processing capabilities, hence guaranteeing efficient and effective quality of service analysis in 5G networks.

4.2 Dataset: The dataset is comprised of four hundred items and eight columns, and it captures a variety of metrics that are associated with the Quality of Service (QoS) of 5G. A date, user ID, application type, signal strength, latency, necessary bandwidth, allocated bandwidth, and resource allocation are all included in each entry. Resource allocation is also included. The signal intensity is measured in decibels per meter, the latency is measured in milliseconds, and the necessary and allotted bandwidth is measured in megabits per second or kilobits per second. The resource allocation is stated as a percentage. For the purpose of measuring quality of service in a 5G network, the application types include everything from phone calls and video calls to streaming and online gaming. This provides a wide collection of use cases.
https://www.kaggle.com/code/snehalsanjaymankar/5g-quality-of-service-mlr-svr-and-knn-regr/input

4.3 Analysis Result

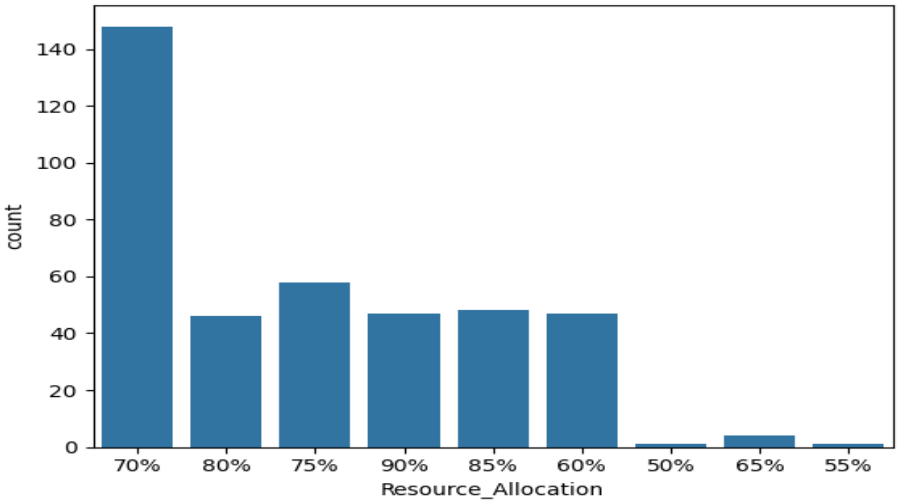

Figure 2. The distribution of resource allocation percentages

4.4 Comprative result

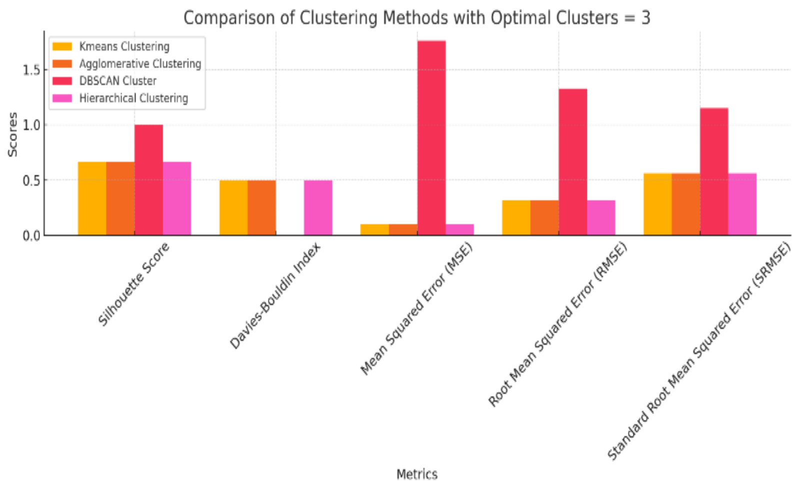

Figure 2. Compares the performance of four clustering methods—K-Means, Agglomerative Clustering, DBSCAN, and Hierarchical Clustering

Figure 2 uses multiple assessment criteria to evaluate K-Means, Agglomerative Clustering, DBSCAN, and Hierarchical Clustering with the ideal number of clusters set to 3. For K-Means, Agglomerative, and Hierarchical Clustering, the Silhouette Score is 0.6638, showing strong cluster separation, whereas DBSCAN scores 1. For K-Means, Agglomerative, and Hierarchical Clustering, the Davies-Bouldin Index is 0.4986, showing strong cluster compactness and separation. DBSCAN scores 0, indicating optimal clustering. DBSCAN has a larger MSE of 1.7608 than K-Means, Agglomerative, and Hierarchical Clustering, which have low prediction error (0.1014). K-Means, Agglomerative, and Hierarchical Clustering have low RMSE and SRMSE (0.3185 and 0.5643, respectively), while DBSCAN has higher values (1.3269 and 1.1519, respectively), indicating more significant errors. In this dataset, K-Means, Agglomerative, and Hierarchical Clustering outperform DBSCAN.

Conclusion

An examination of the Quality of Service (QoS) of 5G using unsupervised machine learning models shows that K-Means, Agglomerative Clustering, and Hierarchical Clustering perform similarly across different evaluation metrics. These models demonstrate effective separation of clusters with Silhouette Scores of approximately 0.6638 and low prediction errors with Mean Squared Errors (MSE) of 0.1014. However, DBSCAN exhibits flawless clustering as seen by a Silhouette Score of 1 and a Davies-Bouldin Index of 0. Nevertheless, it does provide larger values for MSE, RMSE, and SRMSE, suggesting notable inaccuracies in the clustering process. The results indicate that although DBSCAN is proficient at detecting dense clusters and noise, K-Means, Agglomerative, and Hierarchical Clustering exhibit greater consistency and reliability when analyzing 5G QoS parameters. Consequently, these methods are better suited for network optimization and performance management.

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