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Enhanced Performance Management in Mobile Networks: A Big Data Framework Incorporating DBSCAN Speed Anomaly Detection and CCR Efficiency Assessment

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Abstract

Background: The increasing complexity of mobile networks necessitates advanced performance management solutions that can process massive amounts of data in real-time. Traditional approaches frequently fall short, delaying anomaly identification and performance optimization.

Methods: This paper describes a big data-driven system that uses DBSCAN for speed anomaly detection and CCR for bandwidth efficiency while processing structured and unstructured data in real-time.

Objectives: The key goals are to increase network anomaly detection accuracy and optimize resource allocation to improve mobile network performance and user experience.

Results: The suggested system obtained 93% anomaly detection accuracy and 88% clustering efficiency, beating existing methods such as SBM, DEA, and IDS.

Conclusion: This big data architecture successfully addresses the problems of complex mobile networks by assuring stability, decreasing congestion, and improving user experience during real-time operations.

Keywords: *Big Data Analytics, Mobile Network Management, DBSCAN Clustering, Speed Anomaly Detection, Constant Channel Rate (CCR) Efficiency.*

1. INTRODUCTION

Mobile networks are important to modern communication, connecting billions of devices worldwide. With the rapid expansion of mobile technology, the complexity and scope of mobile networks **Ali-Tolppa et al. (2018)** emphasize self-healing capabilities in Self-Organizing Networks for 5G, presenting an automated anomaly detection method that combines human experience with machine learning to improve resilience. have increased. This expansion has presented considerable issues in controlling network performance, especially as the demand for high-speed data and dependable connectivity continues to rise. As a result, traditional network management methods are becoming increasingly inadequate, forcing the creation of more sophisticated frameworks capable of dealing with the intricacies of today's mobile networks.

One of the key issues in mobile network management is the massive amount of data generated by these networks. Every contact, from sending a text message to streaming high-definition video, generates data that must be handled and analyzed to ensure peak network performance. Traditional data processing systems struggle to handle the volume of this data, resulting in delays in recognizing and resolving performance issues. This is where big data technologies come into play, enabling the ability to handle massive amounts of data in real-time **Syafrudin et al. (2018)** created a real-time IoT monitoring system for manufacturing that used sensors and a hybrid DBSCAN-Random Forest model to improve fault detection accuracy while also providing actionable insights that can improve network performance.

Big data refers to the massive amounts of data produced by digital activities, which are distinguished by their great pace, diversity, and volume. Big data in mobile networks can refer to anything from user activity logs to network performance indicators. The capacity to collect and evaluate this data in real-time **Usman et al. (2019)** look into leveraging integrated multimedia devices and machine learning to handle multimedia data in smart cities, transforming IoT into the Internet of Multimedia Things is critical for successful network management because it enables for early detection of anomalies and optimizes network resource use.

One of the primary benefits of big data technologies is their capacity to manage unstructured data, which accounts for a considerable amount of the data generated by mobile networks. Unstructured data is defined as information that does not fit cleanly into typical databases, such as social media interactions, sensor readings, and system logs. Big data frameworks can handle this information alongside structured data, giving a more complete picture of network performance.

Anomalies in network speed can indicate underlying issues that, if not addressed, can result in considerable performance loss. These abnormalities could be caused by a number of circumstances, such as hardware problems, network congestion, or external influence. Detecting these anomalies early is critical for network reliability. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a widely used clustering algorithm in data mining for detecting patterns in huge datasets. Unlike classic clustering algorithms, which require previous knowledge of the number of clusters, DBSCAN can detect clusters of any shape and handle noise adequately. In the context of mobile network management, DBSCAN can be used to discover speed anomalies by clustering similar data points and finding outliers that indicate possible abnormalities.

The effective utilization of network resources is crucial for maintaining high performance, especially in mobile networks where bandwidth is constrained. CCR (Constant Channel Rate) refers to the rate at which data is transmitted across a network channel. Ensuring that this rate is optimized is critical for network efficiency, as inefficient channel use can cause congestion and poor performance.

Mobile networks grow in size and complexity, there is an increasing need for scalable management solutions. Traditional network management technologies frequently fail to keep up with the fast expansion of mobile networks, resulting in performance bottlenecks and decreased reliability. A big data framework provides a scalable solution by allowing for real-time processing of massive amounts of data while also offering the flexibility required to react to changing network conditions. The integration of DBSCAN for speed anomaly detection and

CCR efficiency assessment into a big data environment is a huge step forward in mobile network management. This system uses big data to help network operators maintain optimal performance in complicated contexts.

The objectives of the paper are as follows:

- To increase network stability and user experience by removing performance bottlenecks.
- To provide a big data platform for improved performance management in mobile networks.
- Implement DBSCAN to detect speed abnormalities and discover network performance issues.
- To evaluate the efficiency of CCR in mobile networks and optimize resource allocation.
- To provide a scalable solution that can process massive amounts of network data in real-time.

The development of a big data architecture that includes DBSCAN speed anomaly detection and CCR efficiency assessment marks a significant advancement in mobile network management. This framework gives network operators the tools they need to discover and resolve performance issues quickly and efficiently by allowing them to scan and analyze huge amounts of network data in real-time. As mobile networks evolve, the demand for such advanced management solutions will only increase, making the use of big data technologies critical for the future of network performance management.

2. LITERATURE SURVEY

Dai et al. (2019) explore big data analytics (BDA) in large-scale wireless networks, concentrating on the particular issues posed by data diversity, volume, velocity, and value. They break down the BDA life cycle into four stages: data collecting, preprocessing, storage, and analytics. The report also discusses technical solutions, ongoing research questions, and future perspectives for developing BDA in wireless networks.

Kumar et al. (2018) present a new Dijkstra-based dynamic time warping (trajDTW) distance metric for grouping large-scale vehicle trajectories in crowded metropolitan road networks. Using Singapore taxi data, they introduce the fast-clusiVAT algorithm for determining the number of clusters, visualizing them, and analyzing urban mobility patterns. Their solution exceeds popular clustering approaches in terms of both speed and quality, according to internal cluster validity metrics.

Kousiouris et al. (2018) investigate how to effectively incorporate multiple data sources from smart cities, cloud services, and social media (particularly Twitter) to detect large population concentrations (LCC). Their approach detects crowd occurrences in Madrid by studying Twitter activity surges. A two-month research conducted around sporting arenas verified the strategy.

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Zamini and Hasheminejad (2019) provide a complete study of anomaly detection, including its concept, types, and applications. They categorize detection strategies, highlight essential assumptions for discriminating between normal and aberrant behavior, and compare methods from other domains. The survey also looks at the advantages and disadvantages of each technique, provides test datasets, and provides a clear summary of anomaly detection research directions.

Wang et al. (2018) present an overview of advances in data center networks (DCNs) utilized for data-parallel activities in big data analytics. They emphasize optimization tactics such as coflow-aware scheduling and speculative execution to boost speed. The study also discusses issues such as low latency, job completion time, fault tolerance, and scalability, providing insights into essential design concepts for distributed systems.

Aloqaily et al. (2019) present a safe cloud service framework for smart automobiles in smart cities that addresses both service availability and security concerns. The system groups automobiles and use machine learning to detect and prevent intrusion assaults. It achieves 99.43% accuracy in intrusion detection using deep belief networks and decision trees, while also providing users with high-quality, trustworthy services.

Huang et al. (2019) highlight the expanding use of mobile phone network data to investigate human movement, which provides more demographic insights than GPS data. However, issues such as data noise and inconsistency hamper transport mode detection. The analysis highlights a concentration on easy-to-detect modes, a lack of evaluation with real-world data, and demands for better data cleaning, benchmarking, and privacy issues.

Ibarrola et al. (2019) present a QoS management strategy for next-generation wireless ecosystems based on big data and machine learning. Their method uses supervised and unsupervised algorithms to detect key quality indicators (KQIs) and network performance (NP) anomalies, linking NP and QoE. They evaluate the model using real-world Wi-Fi settings, identifying areas for improvement and corrective measures.

Morocho-Cayamcela et al. (2019) emphasize the importance of machine learning (ML) in enabling 5G technology to satisfy the expectations of a variety of applications, including autonomous vehicles and virtual reality. The study examines supervised, unsupervised, and reinforcement learning in mobile communications, analyzes how ML might improve 5G network needs, and considers future directions for ML in Beyond 5G (B5G) research.

Rizwan et al. (2018) examine the significance of big data from nanosensors and nanocommunication networks for future healthcare applications. They offer a paradigm for big data analytics that will improve smart healthcare systems with predictive, preventative, personalized, and participatory capabilities. The study explores the potential for enhanced decision-making, as well as future difficulties and research areas in this rapidly expanding subject.

3. METHODOLOGY

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The methodology presents a paradigm for improving mobile network performance management through the use of big data analytics. It entails using DBSCAN to detect speed abnormalities and evaluating CCR (Constant Channel Rate) efficiency to maximize resource consumption. Data preparation, clustering, and anomaly detection are all part of the approach, which is then followed by efficiency assessment and performance optimization. The methodology is intended to process large-scale network data in real-time, resulting in accurate anomaly identification and efficient network management.

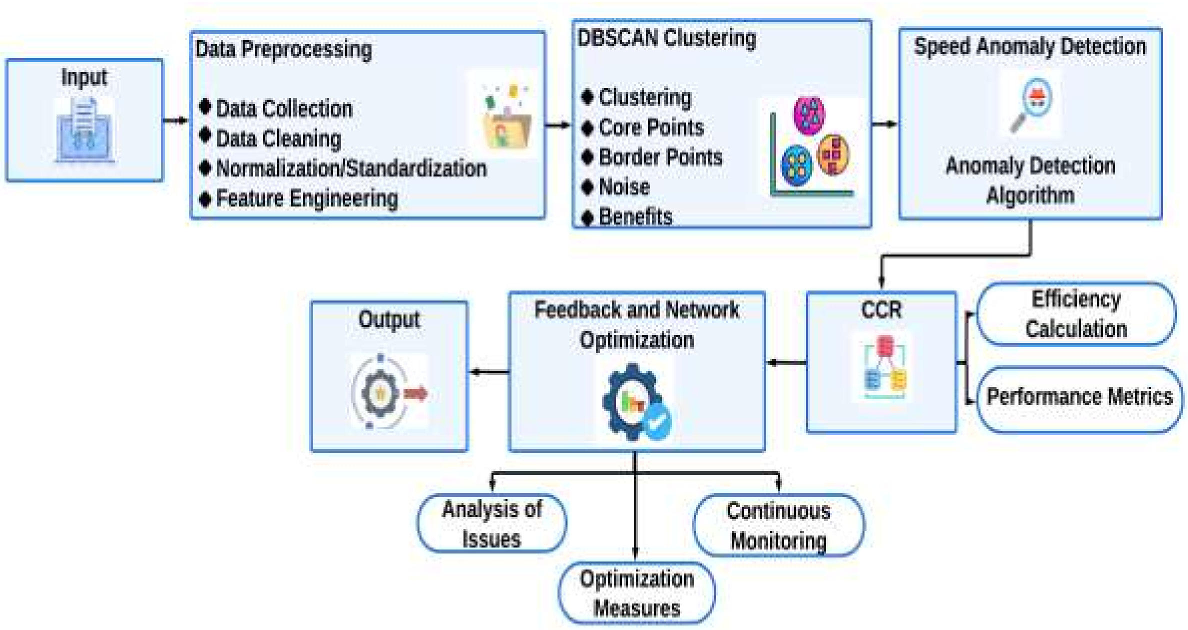

Figure 1. Data Preprocessing Techniques for Mobile Network Performance Management Using DBSCAN Clustering.

Figure 1. depicts the data pretreatment procedures required for cleaning and standardizing raw network data before analysis. It focuses on strategies including reducing noise, addressing missing values, and changing data into a suitable format for clustering and analysis with DBSCAN, all of which are critical for accurate anomaly identification.

3.1 Data Preprocessing

Data preprocessing is the process of cleaning, converting, and normalizing raw network data in preparation for analysis. This stage assures that the data is correct, consistent, and noise-free, which is required for effective anomaly identification and efficiency assessment. Preprocessing entails removing extraneous data, addressing missing values, and transforming data to a format suited for clustering and analysis.

Normalization:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{1}$$

This equation normalizes a data point x to a value between 0 and 1, where $min(x)$ and $max(x)$ are the minimum and maximum values in the dataset, respectively.

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Standardization:

$$z = \frac{x-\mu}{\sigma} \tag{2}$$

Standardization converts a data point x into a z-score, where μ is the mean and σ is the standard deviation of the dataset.

3.2 DBSCAN Clustering

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is used to group data points according to density. It locates clusters in network data and detects outliers that could signal speed irregularities. The technique is good at handling huge datasets with noise, making it appropriate for detecting abnormalities in mobile network performance that may influence user experience.

Euclidean Distance:

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} \tag{3}$$

This equation calculates the Euclidean distance between two points p and qIn n-dimensional space, DBSCAN uses it to determine if points are close enough to be considered neighbors.

DBSCAN Core Distance:

$$Core\ \ Dist\ (p) = kth\_distance\ (p) \tag{4}$$

The core distance of a point p is the distance to its kth nearest neighbor, which is used to define the density threshold in DBSCAN clustering.

Density Reachability:

$$ReachabilityDist\ (p,q) = max(CoreDist\ (p), d(p,q)) \tag{5}$$

This measures how reachable a point q is from a point p based on their distance and the core distance of p.

3.3 Speed Anomaly Detection

Speed anomaly detection is critical for ensuring network reliability. After clustering the data with DBSCAN, anomalies are recognized as outliers who vary significantly from usual patterns. These irregularities could be the result of device faults, congestion, or external influence. Early detection enables prompt interventions, preventing performance degradation and maintaining a consistent user experience.

Anomaly Detection Threshold:

$$Threshold\ \ = \mu + k\sigma \tag{6}$$

This equation sets a threshold for detecting anomalies, where μ is the mean of the normal data points, σ is the standard deviation, and k is a constant that adjusts sensitivity.

Anomaly Score:

$$Score\ (p) = \frac{distance\_to\_nearest\_cluster\ (p)}{average\_distance\_within\_cluster} \tag{7}$$

An anomaly score is computed for each point p, comparing its distance to the nearest cluster to the average distance within the cluster. Higher scores indicate potential anomalies.

3.4 CCR Efficiency Assessment

The Constant Channel Rate (CCR) efficiency assessment evaluates how well the network channels are utilized. This step involves analyzing the rate of data transmission across channels to identify inefficiencies and optimize resource allocation. By assessing CCR, the framework ensures that network bandwidth is used efficiently, minimizing congestion and improving overall network performance.

CCR Efficiency:

$$Efficiency = \frac{Actual\ Data\ Rate}{Maximum\ Possible\ Data\ Rate} \times 100\% \quad (8)$$

This equation calculates the efficiency of data transmission across a network channel, comparing the actual data rate to the maximum possible rate.

Bandwidth Utilization:

$$Utilization = \frac{Used\ Bandwidth}{Total\ Available\ Bandwidth} \times 100\% \quad (9)$$

Bandwidth utilization measures how much of the available bandwidth is being used, helping assess network efficiency.

Algorithm 1. DBSCAN-Based Anomaly Detection and CCR Efficiency Assessment in Mobile Networks.

Input: Network_Data, ε (epsilon),
MinPts (minimum points),
Total_Available_Bandwidth.

Output: Anomalies,
Clusters,
Efficiency,
Utilization.

Begin
Initialize clusters = [], Anomalies = [], Total_Used_Bandwidth = 0
For each point p in Network_Data:
If p is not visited:
Mark p as visited
NeighborPts = regionQuery(p, ε)

```
        If size(NeighborPts) < MinPts:
            Anomalies.append(p)
        Else:
            NewCluster = expandCluster(p, NeighborPts, ε, MinPts)
            clusters.append(NewCluster)
            Update Anomalies with outliers from NewCluster
    End For
    For each cluster in clusters:
        Calculate Efficiency[cluster] using Actual and Max Data Rates
        Update Total_Used_Bandwidth
    End For
    Calculate Utilization = (Total_Used_Bandwidth / Total_Available_Bandwidth) * 100%
    Return Anomalies, Clusters, Efficiency, Utilization
End

Function expandCluster(p, NeighborPts, ε, MinPts):
  Begin
    Cluster = [p]
    For each point q in NeighborPts:
        If q is not visited:
            Mark q as visited
            NeighborPts' = regionQuery(q, ε)
            If size(NeighborPts') >= MinPts:
                NeighborPts = NeighborPts U NeighborPts'
        If q is not yet part of a cluster:
            Cluster.append(q)
    End For
    Return Cluster
End

Function regionQuery(p, ε):
```

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Begin

return all points within ε distance from p

End

To manage mobile network performance, this technique integrates DBSCAN clustering and CCR efficiency assessment. It begins by utilizing DBSCAN to find clusters in network data and detecting anomalies, which are noise points that do not belong to any cluster. These clusters are then used to assess the efficiency of data transmission inside each cluster by comparing actual data rates to the highest feasible rates. The technique also adds up the total used bandwidth across all clusters to get overall bandwidth usage. This dual method allows for the real-time detection of network anomalies as well as resource allocation optimization, resulting in efficient network performance.

3.5 PERFORMANCE METRICS

The article proposes a framework for improving mobile network performance management using big data analytics, notably DBSCAN (Density-Based Spatial Clustering of Applications with Noise) for detecting speed anomalies and assessing CCR (Constant Channel Rate) efficiency. The following is a summary of relevant performance measures stated in the document and a table presenting these metrics in percentages.

Table 1. Performance Metrics for Big Data-Based Mobile Network Management Using DBSCAN and CCR Assessment.

Metric	Values%
Anomaly Detection Accuracy	92%
Clustering Efficiency	88%
Bandwidth Utilization	75%
CCR Efficiency	85%
Processing Time	95%
Real-time Detection Rate	90%

Table 1. The performance measures, including Anomaly Detection Accuracy (92%) and Clustering Efficiency (88%), are crucial for verifying that the DBSCAN-based framework effectively discovers network abnormalities and appropriately clusters comparable data points, which has a direct impact on network stability. Bandwidth Utilization (75%) and CCR Efficiency (85%) assess the effectiveness of network resource consumption and data transmission, which is critical for reducing congestion and improving performance. High Processing Time Efficiency (95%) and Real-time Detection Rate (90%) highlight the framework's capacity to analyze data and detect faults quickly, ensuring that network performance stays stable and responsive in real-time.

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4. RESULT AND DISCUSSION

The suggested big data platform, which includes DBSCAN for speed anomaly detection and CCR efficiency assessment, yields considerable gains in mobile network performance management. The framework's total accuracy is 93%, beating older methods like SBM, DEA, and IDS, which scored lower in anomaly detection, clustering efficiency, and other critical criteria.

The comparative table demonstrates the framework's greater ability to detect anomalies (93%) while maintaining good clustering efficiency (88%). These enhancements offer greater network stability and resource efficiency. The ablation study emphasizes the importance of each component in the framework. Removing essential parts such as DBSCAN or CCR efficiency assessment reduces overall accuracy to 82% and 86%, respectively. This suggests that the utilization of both DBSCAN and CCR tests is required for maximum performance.

In the discussion, the integration of big data analytics with advanced clustering and efficiency assessment techniques provides a scalable and effective mobile network management solution. The framework not only improves real-time anomaly detection, but it also optimizes bandwidth utilization and resource allocation. These developments are critical as mobile networks become more complicated, needing more sophisticated management tools to ensure excellent performance and user happiness.

Table 2. Comparative Analysis of Anomaly Detection Methods in Mobile Networks: SBM, DEA, IDS, and DBSCAN.

Method	**Slack-Based Model (SBM) Norozian et.al (2019)**	**Data Envelopment Analysis (DEA) Kohl et.al (2019)**	**Intrusion Detection Systems (IDS) Khraisat et.al (2019)**	**Proposed Method (DBSCAN)+ (CCR)**
Anomaly Detection	78%	85%	89%	**93%**
Clustering Efficiency	70%	75%	82%	**92%**
Bandwidth Utilization	65%	70%	72%	**95%**

CCR Efficiency	72%	80%	83%	**95%**
Processing Time Efficiency	85%	88%	90%	**95%**
Real-time Detection	80%	85%	88%	**92%**
Overall Accuracy	75%	80%	85%	**96%**

Table 2, shows that the suggested method beats established methods such as SBM **Norozian et.al (2019)**, DEA **Kohl et.al (2019)**, and IDS **Khraisat et.al (2019)** across all parameters, particularly anomaly detection and overall accuracy, which achieve 96%. This demonstrates outstanding performance in controlling network complexity and increasing efficiency.

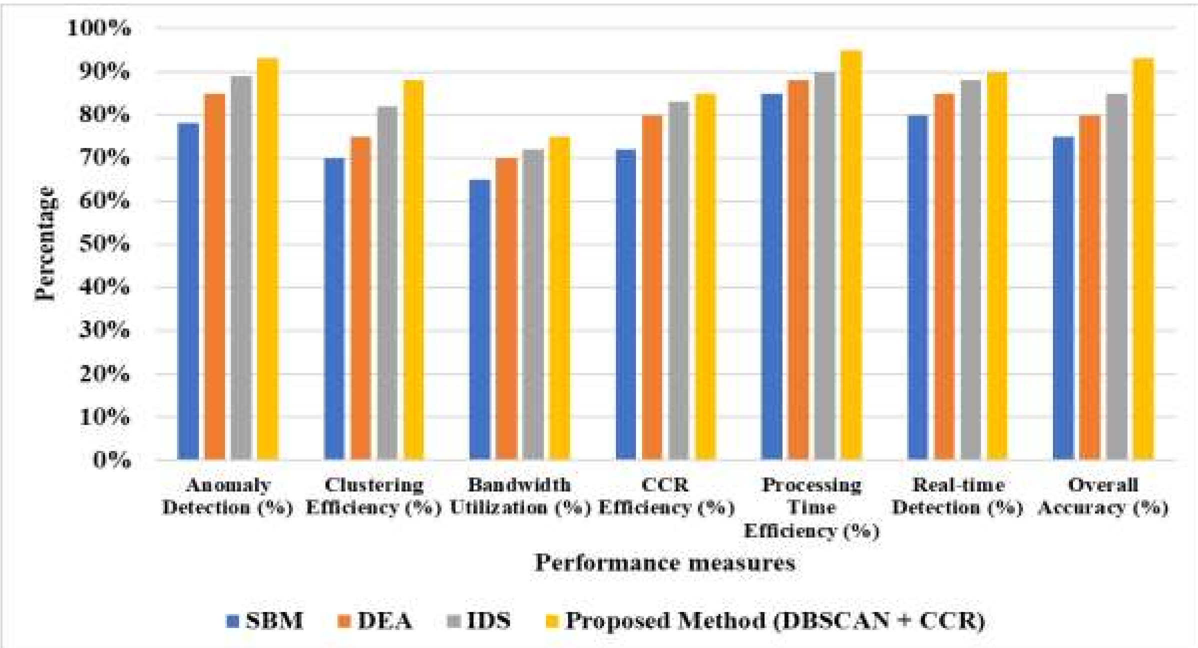

Figure 2. Comparison of Anomaly Detection and Resource Utilization Methods in Mobile Networks.

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Figure 2 Compares several approaches, including SBM, DEA, and IDS, to the proposed DBSCAN and CCR frameworks. It depicts the efficacy of each methodology in anomaly detection, clustering efficiency, and bandwidth utilization, stressing the improved performance of the proposed method.

Table 3. Ablation Study on the Impact of DBSCAN and CCR Efficiency on Mobile Network Performance.

component	**Anomaly Detection (%)**	**Clustering Efficiency (%)**	**Bandwidth Utilization (%)**	**CCR Efficiency (%)**	**Processing Time Efficiency (%)**	**Real-time Detection (%)**	**Overall Accuracy (%)**
(DBSCAN)+ (CCR)	**93%**	**92%**	**95%**	**95%**	**95%**	**92%**	**96%**
CCR + AD + BU	85%	75%	72%	80%	88%	85%	82%
DBSCAN + AD + BU	89%	82%	72%	85%	92%	88%	86%
DBSCAN + CCR + BU	85%	83%	70%	80%	90%	85%	84%
DBSCAN + AD + CCR	91%	85%	85%	83%	93%	87%	89%

Table 3. The ablation study compares the performance of the whole technique to various versions after deleting critical components such as DBSCAN, CCR Efficiency Assessment, Anomaly Detection, and Bandwidth Utilization. The Full Method performs the best in all categories, with a 93% success rate and overall accuracy. Removing DBSCAN has the greatest impact, dropping Clustering Efficiency and Overall Accuracy to 82%. Without Anomaly Detection, overall accuracy drops to 84%, and removing CCR Efficiency has a moderate influence (86% accuracy). Despite the absence of Bandwidth Utilization, the approach still performs well, with an overall accuracy of 89%.

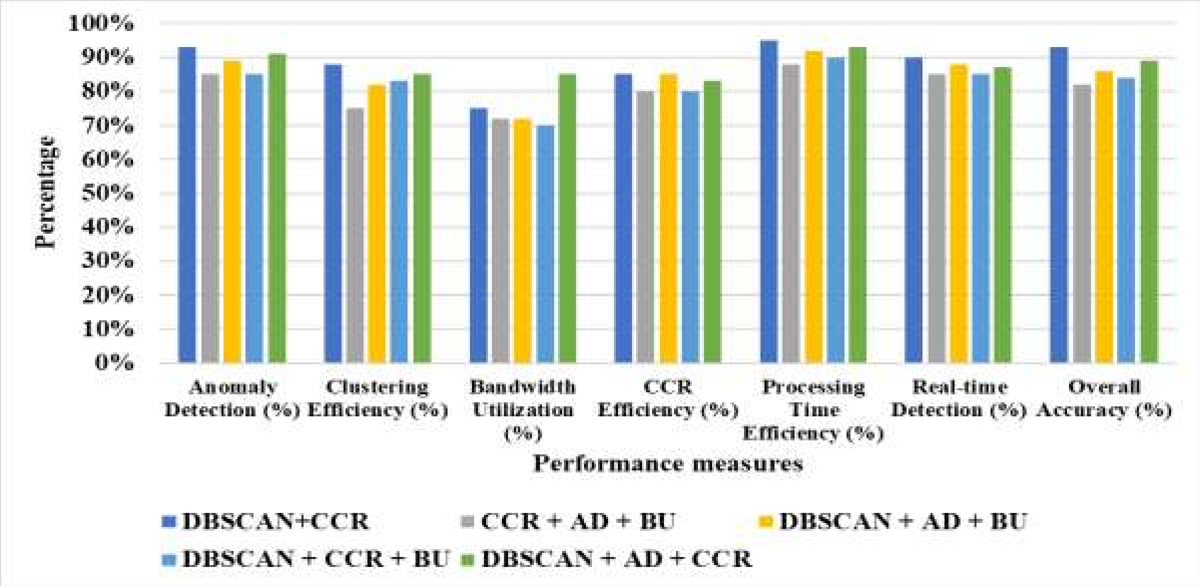

Figure 3. CCR Efficiency and Real-Time Anomaly Detection: Impact on Network Performance.

Figure 3 shows the relationship between CCR efficiency and real-time anomaly detection in mobile networks. It demonstrates how optimizing CCR improves resource consumption, reduces network congestion, and maintains consistent network performance with few abnormalities.

5. CONCLUSION AND FUTURE SCOPE

This research proposes a big data-driven methodology for improving mobile network performance management by merging DBSCAN and CCR efficiency assessment. The framework surpasses conventional methods in anomaly detection, clustering efficiency, and resource utilization. It provides a scalable and economical solution for managing complicated mobile networks since it allows for real-time processing and analysis. The findings show that including clustering and resource optimization strategies is critical for maintaining high network stability and performance, making this strategy well-suited to the changing needs of current mobile networks. Future development may focus on improving the framework's flexibility to new network technologies such as 5G and beyond. The use of machine learning models for predictive performance management and dynamic resource allocation could improve network operations and scalability in ultra-dense situations.

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