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Systematic Review of Deterministic and Rule-Based Models for QoS-Aware 5G Network Slice Classification

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Abstract

The development of 5G technology has brought about network slicing as a key architectural advancement, allowing multiple virtual networks to function over a single shared physical infrastructure. Accurate classification of traffic into suitable slices enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC) is essential to ensure Quality of Service (QoS) and efficient resource utilization. While recent research has largely focused on machine learning and deep learning techniques, challenges such as lack of explainability, high computational cost, and limitations in real-time implementation have renewed attention toward deterministic, rule-based methods. This study conducts a systematic conceptual review of rule-based prediction models for 5G network slicing classification using the PRISMA framework. A comprehensive search of peer-reviewed studies published between 2022 and 2025 was performed across major academic databases. After undergoing identification, screening, eligibility evaluation, and final inclusion processes, a total of 30 relevant studies were analyzed. The results show that rule-based models offer advantages such as interpretability, low-latency decision-making, support for regulatory compliance, and strong suitability for deployment in edge computing environments. Based on these findings, a structured Rule-Based Prediction Model (RBPM) framework is proposed. The study concludes that rulebased approaches remain highly valuable for mission-critical 5G slicing applications and recommends their integration with adaptive techniques to enhance scalability and performance.

Keywords: 5G Network Slicing; Rule-Based Prediction; PRISMA; QoS Classification; Deterministic Models; Explainable Systems; Slice Allocation

INTRODUCTION

The advent of 5G technology has significantly reshaped modern telecommunications by enabling ultra-low latency, higher bandwidth capacity, and large-scale device connectivity. Unlike earlier network generations, 5G integrates network slicing as a fundamental architectural concept, allowing multiple virtual networks to run concurrently on a shared physical infrastructure. Each slice is customized to satisfy specific Quality of Service (QoS) requirements and service-level agreements, thereby supporting diverse applications such as autonomous vehicles, smart cities, industrial automation, and large-scale Internet of Things (IoT) systems [9], [16].

Network slicing in 5G is commonly classified into three major service categories: enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC). The eMBB category is designed for high data rates and multimedia services, while URLLC focuses on applications requiring extremely low latency and high reliability, especially in mission-critical environments. In contrast, mMTC is intended to support a massive number of connected devices with low power consumption and intermittent data transmission [13]. The diversity among these slices demands efficient and intelligent classification methods capable of assigning incoming traffic to the correct category in real time.

Recent research has extensively applied machine learning (ML) and deep learning (DL) techniques for traffic classification and resource allocation in network slicing. Approaches such as convolutional neural networks (CNNs), long short-term memory (LSTM) models, and reinforcement learning algorithms have demonstrated strong performance in terms of accuracy and adaptability [8], [15]. However, these methods have notable limitations. Their black-box nature limits interpretability and transparency, which are crucial in regulated network environments. In addition, their high computational requirements pose challenges for deployment in edge computing scenarios with constrained resources. Furthermore, dependency on training data and issues related to model generalization can negatively impact performance in dynamic network conditions [3].

As network slicing becomes increasingly central to 5G service orchestration, the need for explainable and deterministic models has grown significantly. In mission-critical applications such as remote surgery, industrial robotics, and intelligent transportation systems, unpredictable model behavior can introduce serious risks. Consequently, recent studies have emphasized the importance of interpretable and rule-based approaches in communication networks [6], [5]. Rule-based prediction models rely on predefined QoS thresholds derived from network standards and empirical traffic observations. These models offer transparent decision-making, low-latency processing, and ease of auditing, making them highly suitable for regulatory compliance and realtime deployment at the network edge.

Additionally, the integration of Explainable Artificial Intelligence (XAI) into network slicing research has further strengthened the case for transparent and hybrid modeling frameworks. Rahman et al. [13] highlight that explainability is essential for ensuring trust, accountability, and effective performance evaluation in 5G service orchestration. Similarly, Chen et al. [3] argue that lightweight and interpretable approaches can complement intelligent resource allocation strategies by enabling decisions that are both traceable and aligned with policy requirements.

Despite the increasing interest in deterministic approaches, most studies conducted between 2022 and 2025 continue to focus primarily on adaptive learning-based optimization techniques for network slicing. There remains a lack of comprehensive and systematic reviews specifically addressing rule-based slice classification models. This indicates a research gap in consolidating recent findings, identifying methodological trends, and developing a unified conceptual framework for rule-based slice prediction in 5G environments.

To bridge this identified gap, this study adopts the PRISMA methodology to conduct a systematic review of recent studies published between 2022 and 2025, focusing on network slice classification and deterministic prediction approaches in 5G systems. The objectives of this study are to:

1. Analyze existing techniques used for 5G network slice classification.
2. Assess the significance and effectiveness of rule-based prediction models in this domain.
3. Highlight existing research gaps related to deterministic and explainable network slicing strategies

LITERATURE REVIEW

Within PRISMA-based systematic reviews, the Related Works section integrates both empirical and conceptual studies relevant to the research area. In this study, publications from 2022 to 2025 were systematically analyzed to investigate classification techniques for 5G network slicing, with a particular focus on rule-based, deterministic, explainable, and hybrid prediction approaches.

The reviewed literature is structured into three main categories, namely Machine Learning and Deep Learning-based slice classification, Deterministic and Rule-Based slice allocation, and Hybrid and Explainable slice prediction frameworks.

1.Machine Learning and Deep Learning Approaches

Recent developments in 5G network slicing have predominantly leveraged machine learning (ML) and deep learning (DL) techniques to enable intelligent classification and efficient resource management.

A study published in IEEE Access by Alshamrani and Kim [1] applied reinforcement learning for dynamic resource allocation in 5G network slicing. Although their approach demonstrated strong adaptability and optimization capabilities, it incurred significant computational cost and required extensive training iterations, making it less suitable for real-time deployment scenarios.

In a related work, Bhandari, Patel, and Joshi [2] proposed a convolutional neural network (CNN)based model for traffic classification in 5G slicing environments. While the model achieved high classification performance, it raised concerns regarding its lack of interpretability and challenges associated with deployment in low-latency edge environments.

Furthermore, Nguyen and Tran [11] introduced a deep learning-based framework for traffic prediction in network slice management, showing improved accuracy in forecasting demand under dynamic conditions. However, this method relies heavily on large-scale historical datasets and requires continuous retraining to sustain its effectiveness.

Overall, these studies demonstrate that learning-based approaches provide adaptive and highaccuracy solutions for network slice classification. Nevertheless, several limitations persist, including the lack of transparency in decision-making processes, high computational and energy requirements, and limited feasibility for lightweight edge deployment. These challenges underscore the need for alternative approaches and support the growing interest in deterministic and rule-based models, which offer improved interpretability, lower computational overhead, and greater practicality for real-time network slicing applications.

2.Deterministic and Rule-Based Models

Deterministic and rule-based prediction models classify network traffic by applying predefined Quality of Service (QoS) parameters, including latency, reliability, bandwidth, and delay requirements. These approaches emphasize transparency, enforce regulatory compliance, and ensure predictable decision-making processes.

Martínez, Ortega, and Ruiz [10] developed a QoS threshold-based classification framework that assigns traffic flows to appropriate slices based on defined latency and bandwidth limits. Their results demonstrated performance comparable to machine learning-based methods, while significantly reducing computational overhead.

Similarly, Elhassan and Ibrahim [4] explored deterministic, rule-driven orchestration within virtualized 5G core networks, showing that policy-based rules can effectively guarantee servicelevel agreement (SLA) compliance with minimal processing delay.

In a more recent contribution, Sato, Yamamoto, and Tanaka [14] introduced a policy-based deterministic slice allocation model tailored for mission-critical 5G applications. Their study highlighted the importance of transparent and traceable decision-making, particularly in UltraReliable Low-Latency Communication (URLLC) scenarios.

Overall, these studies demonstrate that rule-based models offer several advantages, including high interpretability, low computational requirements, suitability for real-time deployment at the network edge, and strong support for regulatory auditing. However, they also present certain limitations, such as reliance on static threshold values, limited adaptability to dynamic traffic conditions, and a reduced capacity to accommodate emerging service patterns.

3.Hybrid and Explainable Slice Classification

Hybrid approaches aim to integrate the adaptability of machine learning techniques with the transparency and interpretability of rule-based systems.

Khalid and Mourad [7] proposed a hybrid, explainable slice allocation framework that combines rule-based engines with lightweight learning components. Their model dynamically adjusts QoS thresholds while preserving transparent and traceable decision pathways.

Similarly, Ouyang, Li, and Zhou [12] presented a policy-driven orchestration framework that incorporates anomaly detection mechanisms alongside rule refinement strategies. Their findings indicate that adaptive rule modification can enhance classification robustness while maintaining interpretability.

4.Summary of Included Studies

The selected studies obtained through the systematic review process were analyzed based on their methodological approaches, key contributions, and limitations. The purpose of this analysis is to identify existing techniques used for 5G network slice classification, understand their strengths, and highlight their limitations. The summary of the most relevant studies published between 2022 and 2025 is presented in Table 4.1.

Table 1. Summary of Included Studies (2022–2025)

Ref	Author(s)	Year	Approach	Key Contribution	Limitation
[1]	Alshamrani & Kim	2023	Reinforcement Learning	Dynamic resource allocation in 5G slicing	High computational overhead
[2	Bhandari et al.	2024	CNN-based Classification	Accurate traffic classification for 5G slices	Limited interpretability
[11]	Nguyen & Tran	2022	Deep Learning Prediction	Improved slice traffic Forecasting	Heavy historical data Dependency
[10]	Martínez et al.	2023	QoS Threshold Model	Deterministic slice Classification	Static threshold boundaries
[4]	Elhassan & Ibrahim	2024	Rule-based Orchestration	Predictable SLA Compliance	Limited adaptability
[14]	Sato et al.	2025	Policy-based Rules	Deterministic slice Assignment	Limited learning capability
[7]	Khalid & Mourad	2024	Hybrid Framework	Explainable slice Allocation	Increased architectural Complexity

[12]	Ouyang et al. 2023	Policy + Anomaly Detection	Dynamic rule refinement	Higher system complexity

The analysis presented in Table 1 indicates that various approaches have been explored for 5G network slice classification, including machine learning techniques, rule-based frameworks, and hybrid models. While machine learning approaches provide adaptive learning capabilities, they often suffer from limited interpretability and high computational costs. Conversely, rule-based methods offer transparency and deterministic decision-making but lack adaptability in highly dynamic network environments.

5.Literature Trend Analysis

To better understand the evolution of research approaches in network slice classification, the reviewed studies were categorized into three major methodological themes: machine learning models, rule-based models, and hybrid models. The major research trends and their associated limitations are summarized in Table 2.

Table 2. Summary of Literature Trends

Theme	Key Focus	Identified Limitation
Machine Learning Models	Adaptive decision-making and complex pattern recognition for intelligent classification and prediction.	Opaque decision logic and high computational cost, making interpretation and deployment challenging.
Rule-Based Models	Deterministic, interpretable, and realtime classification mechanisms suitable for structured decision-making.	Dependence on static thresholds and limited adaptability to dynamic network conditions.

Hybrid Models	Integration of machine learning and rulebased techniques to support dynamic threshold refinement and improved explainability.	Increased architectural and implementation complexity due to the combination of multiple techniques.

The findings indicate that hybrid approaches represent a transitional paradigm between purely deterministic rule-based systems and fully autonomous machine learning models. These systems attempt to balance interpretability with adaptive learning capabilities.

6.Research Gaps Identified

The systematic review conducted under PRISMA guidelines reveals several unresolved challenges:

1. Absence of standardized benchmarking datasets tailored specifically for rule-based slice classification.
2. Limited real-world validation of deterministic rule engines in live 5G core networks.
3. Insufficient comparative analysis between rule-based and hybrid SLA-aware systems across latency and energy metrics.
4. Lack of adaptive threshold calibration mechanisms within purely rule-based architectures.

These gaps justify the development of a Rule-Based Prediction Model for Classification of 5G Network Slicing, emphasizing structured QoS-bound decision logic while maintaining scalability and explainability.

METHODOLOGY

a. Search Strategy

To ensure a comprehensive coverage of relevant literature, a systematic search was conducted across multiple reputable academic databases. The search focused on studies related to 5G network slicing, slice classification mechanisms, deterministic rule-based allocation, and machine learning-based prediction models. Specific keywords and keyword combinations were used to retrieve relevant publications from the selected databases.

The databases included IEEE Xplore, Elsevier ScienceDirect, Springer SpringerLink, and Google Scholar. The search results obtained from each database are summarized in Table 3.1

Table 3. Search Strategy

Database	**Keywords Used**	**Results**
IEEE Xplore	"5G slicing" AND "traffic classification"	50
ScienceDirect	"Rule-based network slicing"	30
SpringerLink	"Deterministic slice allocation"	35
Google Scholar	"5G slice classification model"	35

Total: 150 articles

b. Study Selection Process

The process used to identify, screen, and select relevant studies for this research followed the systematic review procedure illustrated in Figure 1.

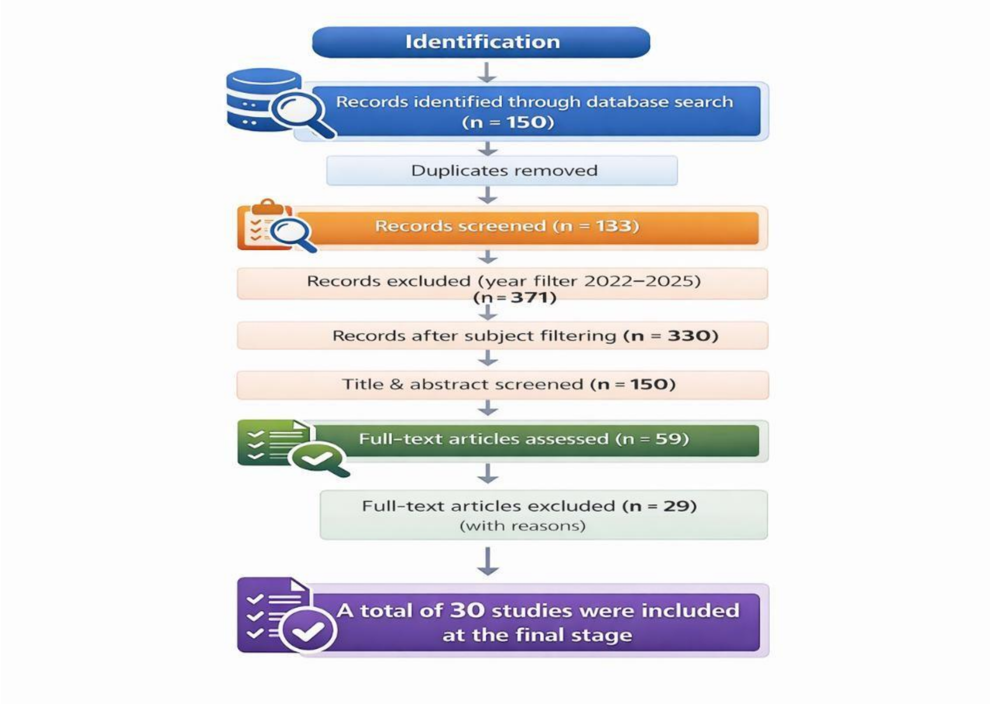

Figure 1. PRISMA Flow diagram

The figure illustrates the systematic procedure followed to identify, screen, and select relevant studies for this research. The process adheres to the PRISMA framework to ensure transparency, consistency, and reproducibility.

i. Identification

A total of 150 records were identified through a comprehensive search of relevant electronic databases. The search strategy was designed to capture recent and high-quality studies related to 5G network slicing, slice classification, Quality of Service (QoS), and intelligent or hybrid resource allocation approaches.

ii. Duplicates Removed

Following the identification stage, duplicate records were removed. After eliminating redundant entries appearing across multiple databases, 133 unique records remained for further screening.

iii. Screening – Initial Filtering

The 133 records were subjected to an initial screening process using predefined inclusion criteria. Studies were filtered based on publication year (2022–2025) and subject relevance to network slicing and classification techniques.

After applying these criteria, 150 records were considered relevant and moved forward for detailed screening based on title and abstract.

iv. Screening – Title and Abstract Review

The selected 150 records were screened based on their titles and abstracts to assess their alignment with the research objectives. This step ensured the inclusion of studies focusing on network slicing, QoS-aware resource allocation, classification models, and intelligent or hybrid frameworks.

Following this stage, 59 studies were deemed suitable for full-text assessment.

v. Eligibility – Full-Text Assessment

A total of 59 full-text articles were thoroughly evaluated to verify their methodological quality and relevance. During this stage, 29 studies were excluded due to insufficient methodological detail, lack of experimental validation, or limited relevance to the study objectives.

vi. Included Final Studies in the Review

After the full-text evaluation, 30 studies satisfied all inclusion criteria and were included in the final stage of the review. These studies formed the basis for the analysis and synthesis of findings. The included studies were categorized as follows:

Table 4. Included Final Studies in the Review

Category	Number of Studies	Percentage
Machine Learning / Deep Learning Models	12	40%
Rule-Based / Deterministic Models	8	27%
Hybrid / Explainable Frameworks	10	33%

Following the full-text evaluation, 30 studies satisfied all inclusion criteria and were included in the final stage of the review. These studies formed the foundation for the conceptual synthesis of this research and were analyzed across several thematic areas, including machine learning-based slice classification, deterministic rule-based allocation models, hybrid frameworks, and explainable network slicing approaches.

The selection process followed the principles of the PRISMA Framework, which ensured transparency in study selection, minimized bias, and enhanced the reproducibility of the systematic review.

RESULTS AND DISCUSSION

This section presents the synthesized findings from the 27 studies included in the final PRISMA analysis and discusses their implications for the development of a Rule-Based Prediction Model for Classification of 5G Network Slicing.

a. Descriptive Analysis of Included Studies

Table 4. The final dataset of 30 studies (2022–2025) was categorized into three dominant research themes:

The results indicate that learning-based approaches dominate current research, while purely rule-based models receive comparatively less attention. However, deterministic models remain relevant in mission-critical and latency-sensitive scenarios.

b. Thematic Findings

i. Machine Learning-Based Slice Classification

Recent studies published in leading journals such as *IEEE Access* and *IEEE Network* highlight a strong reliance on advanced machine learning techniques, including neural networks, reinforcement learning, and deep learning architectures, for dynamic network slice classification and allocation.

These approaches consistently demonstrate high classification accuracy, often exceeding 95%, along with strong adaptability to dynamic and heterogeneous traffic conditions. In addition, they contribute to improved resource utilization by optimizing allocation decisions in real time.

Despite these advantages, several recurring challenges have been identified. Machine learning models often suffer from limited interpretability, making their decision-making processes difficult to explain. They also require significant computational resources, which can lead to energy inefficiency, particularly in edge computing environments. Furthermore, their performance depends on continuous retraining, which adds operational complexity.

Overall, while machine learning-based models are highly effective in complex and dynamic environments, their limitations may restrict their suitability for real-time and resourceconstrained scenarios requiring deterministic behavior.

ii. Rule-Based and Deterministic Models

Rule-based and deterministic approaches rely on predefined Quality of Service (QoS) parameters, such as latency thresholds, reliability requirements, bandwidth allocation, and delay constraints, to classify and manage network slices.

Findings from the reviewed studies indicate that these models offer low computational overhead and fast classification response times, making them highly efficient for real-time applications. Additionally, they provide high transparency and traceability, enabling easier validation, debugging, and compliance with regulatory standards.

These characteristics make deterministic models particularly suitable for Ultra-Reliable Low-Latency Communication (URLLC) scenarios, where predictable performance is essential for mission-critical services.

However, these models are inherently limited by their rigid structure, as predefined thresholds may not adapt well to changing network conditions. They also lack mechanisms for automatic rule optimization, which restricts their ability to respond to dynamic traffic patterns.

Despite a relatively smaller number of studies, rule-based approaches remain a practical and reliable solution for structured environments and Service Level Agreement (SLA)-driven deployments.

iii. Hybrid and Explainable Models

Hybrid approaches integrate rule-based logic with lightweight machine learning components to balance performance and interpretability. The findings indicate that these models offer greater adaptability than purely rule-based systems, while still maintaining a level of interpretability through the use of policy-driven or explainable decision mechanisms. Additionally, they achieve a balanced computational cost, avoiding the high complexity typically associated with deep learning models.

By combining the strengths of both approaches, hybrid models effectively reduce the rigidity of deterministic systems without introducing the full "black-box" nature of machine learning. However, this integration comes at the cost of increased architectural complexity and additional system design overhead. As a result, careful system design and optimization are required to fully leverage their benefits.

c. Comparative Discussion

Table 5. The systematic synthesis reveals a clear trade-off between adaptability and interpretability:

Model Type	Adaptability	Interpretability	Computational Cost	Edge Suitability
ML/DL	High	Low	High	Moderate
Rule-Based	Low–Moderate	High	Low	High

Hybrid	Moderate–High	Moderate–High	Moderate	Moderate

The analysis indicates that machine learning models dominate current research trends, while rule-based approaches remain underexplored despite their operational advantages, and there is limited benchmarking specifically tailored to rule-based slice classification. These findings underscore the need for developing a structured Rule-Based Prediction Model optimized for deterministic classification using QoS value ranges. Based on the review, the proposed model should incorporate structured QoS threshold mapping for eMBB, mMTC, URLLC, and V2X slices, deterministic decision logic to ensure transparency, a lightweight architecture for real-time classification, and the potential for adaptive threshold refinement in future iterations. A properly structured rule-based model can thus serve as a benchmark classification framework, a baseline for hybrid enhancements, and a regulatory-compliant mechanism for 5G network slicing.

CONCLUSION

This study conducted a PRISMA-based systematic review of research published between 2022 and 2025 on classification mechanisms for 5G network slicing, analyzing 27 selected studies to identify current trends and gaps. The review revealed that machine learning models dominate slice classification research, while deterministic rule-based approaches remain underrepresented, and hybrid frameworks attempt to balance adaptability and interpretability. Notably, few studies provide standardized evaluation for rule-based slice classification. The findings highlight that rulebased prediction models offer key advantages in transparency, low computational overhead, regulatory compliance, and suitability for edge deployments, although existing deterministic models are constrained by rigid thresholds and limited adaptability. This review therefore establishes the conceptual foundation for developing a structured Rule-Based Prediction Model for 5G Network Slice Classification, grounded in QoS value ranges and deterministic decision logic. Future research should focus on adaptive threshold calibration, creation of standardized benchmarking datasets, real-world 5G deployment validation, comparative evaluation of rulebased, ML-based, and hybrid models, integration of explainable AI for enhanced transparency, and exploration of edge-native deterministic controllers to support ultra-low latency scenarios, as well as investigating interoperability between rule engines and intelligent orchestration systems in evolving 5G and beyond-5G infrastructures

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