IJEMD-CSAI, 4 (1) (2025) https://doi.org/ 10.54938/ijemdcsai.2025.04.2.540

International Journal of Emerging Multidisciplinaries: Computer Science and Artificial Intelligence

Research Paper
Journal Homepage: www.ojs.ijemd.com
ISSN (print): 2791-0164 ISSN (online): 2957-5036

Enhanced Slice Prediction In 5G Network using Ensemble-Based Classification

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Abstract

The evolution of 5G networks has introduced the need for intelligent network slicing to support diverse service requirements such as enhanced Mobile Broadband (eMBB), massive MachineType Communications (mMTC), Ultra-Reliable Low-Latency Communications (URLLC), and vehicular applications (V2X). In this study, preprocessing steps were applied, including data cleaning, reclassification of slice attributes, integration of V2X parameters from literature, and feature encoding to define four slice categories. Following feature selection and a 70/30 Train-Test Split, machine learning models were developed for slice classification. The Random Forest model achieved an accuracy of 0.987, while Gradient Boosting recorded 0.986, demonstrating strong predictive capability and generalization. These findings highlight the effectiveness of ensemble learning techniques for precise 5G slice identification and support the advancement of intelligent network management frameworks.

Keywords: 5G, Network Slicing, Machine Learning, Random Forest, Gradient Boosting.

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Introduction

In today's fast-evolving digital landscape, the collaboration between telecommunications providers and technology enterprises has fueled a relentless pursuit of innovative solutions to address the growing demand for mobile data [5]. One of the most transformative outcomes of this evolution is the emergence of fifth-generation (5G) mobile communication technologies, which introduce ultra-fast data speeds, high network capacity, and extremely low [2]. The rapid increase in mobile data consumption and device connectivity has positioned 5G as the foundation for future digital ecosystems, supporting services such as smart cities, industrial automation, and real-time applications [18]. With its advanced capabilities, 5G networks are expected to reshape not only communications but also the way industries operate and deliver services [11]. For consumers, 5G provides enhanced accessibility, reliability, and services such as telemedicine and remote education [12]. Industries benefit from the potential for process automation, operational efficiency, and data-driven decision-making [13]. On an economic level, 5G deployment is projected to generate new revenue opportunities and employment prospects across multiple sectors [15]. The progression to 5G is part of a historical trajectory of mobile network development. The first generation (1G) provided costly analog voice services with limited coverage. Second-generation (2G) introduced digital voice and SMS, expanding access and usage [9]. The third generation (3G) brought mobile internet, email, and multimedia services, while fourth-generation (4G) networks delivered high-speed broadband, enabling app-driven ecosystems and large-scale data streaming [7].

Modern 5G networks build upon these advances with technologies such as massive MIMO, network slicing, virtualization, and edge computing [6]. These capabilities support service-specific architectures, improve network flexibility, and enhance overall performance [4]. Together, they mark a significant milestone in the evolution of mobile communication, positioning 5G as the backbone of the next digital revolution.

This paper presents the following key contributions:

Identification of key features essential for accurate prediction of 5G network slice types, including emerging V2X services.

Development and evaluation of machine learning models, specifically ensemble algorithms, for classifying 5G slices into eMBB, mMTC, URLLC and V2X categories.

Comprehensive performance assessment using metrics such as Accuracy, Precision, Recall, F1score and AUC to validate model effectiveness in intelligent slice prediction.

The remainder of this paper is structured as follows: Section 2 reviews related work; Section 3 outlines the methodology; Section 4 discusses the results and findings; and finally, Section 5 concludes the paper.

Related Work

Machine learning has gained significant attention in the field of 5G network slicing due to its ability to enhance automation, optimize resource allocation, and improve Quality of Service (QoS). Recent studies have explored various techniques, including supervised learning, deep learning, and reinforcement learning, to enable intelligent slice classification and management. These approaches aim to address the growing demands of services such as eMBB, mMTC, URLLC, and V2X within modern communication networks.

In this context, [3] introduced two algorithms to optimize the deployment of core network functions in both 4G and 5G infrastructures. The first algorithm leveraged Mixed Integer Linear Programming (MILP) to maximize operational efficiency, while the second employed coalition formation games to strategically position network functions (e.g., SMF, AMF, PGW, AUSF) within cloud environments. Their approach enhanced Quality of Service (QoS), stabilized operational costs, and improved cloud provider revenues.

[8] proposed a hybrid framework that integrates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks for 5G network slice classification. In their design, CNNs extracted spatial features for classification, while LSTMs performed statistical analysis of sequential data. This combination improved accuracy and efficiency in slice classification while providing deeper insights into resource allocation and utilization in modern communication systems.

[14] identified essential elements for effective network slicing, including slice-specific learning and prediction, reinforcement learning-based optimization, traffic and mobility analysis, and admission control guided by spatial data. They developed the RL-NSB framework, which adapts dynamically to user distribution and traffic patterns. The framework significantly improved system utilization while ensuring compliance with Service Level Agreements (SLAs).

[17] designed a machine learning–driven approach for dynamic resource scheduling in network slicing, focusing on reliability and efficiency of service delivery. By employing Deep Reinforcement Learning (DRL), their model effectively addressed privacy concerns and optimized resource allocation across multiple slices. Simulation outcomes demonstrated its ability to satisfy QoS demands dynamically while maintaining user-centered decision-making.

[10] proposed VIKOR-CNSP, a heuristic algorithm based on the VIKOR Multi-Criteria DecisionMaking (MCDM) technique for provisioning 5G core network slices. Their approach evaluated nodes using both topological and resource-based factors, selected high-ranking nodes, and applied shortest-path optimization for slice link allocation. The method achieved higher acceptance rates, favorable revenue-to-cost ratios, and compliance with stringent security constraints.

[16] introduced Deep Slice, a deep learning–based technique for enhancing network availability and load balancing. By analyzing Key Performance Indicators (KPIs), their model predicted optimal slice allocations for previously unidentified device types. The system demonstrated

intelligent resource allocation, efficient usage of standard slices, and resilience under failure conditions, thereby ensuring robust network operations.

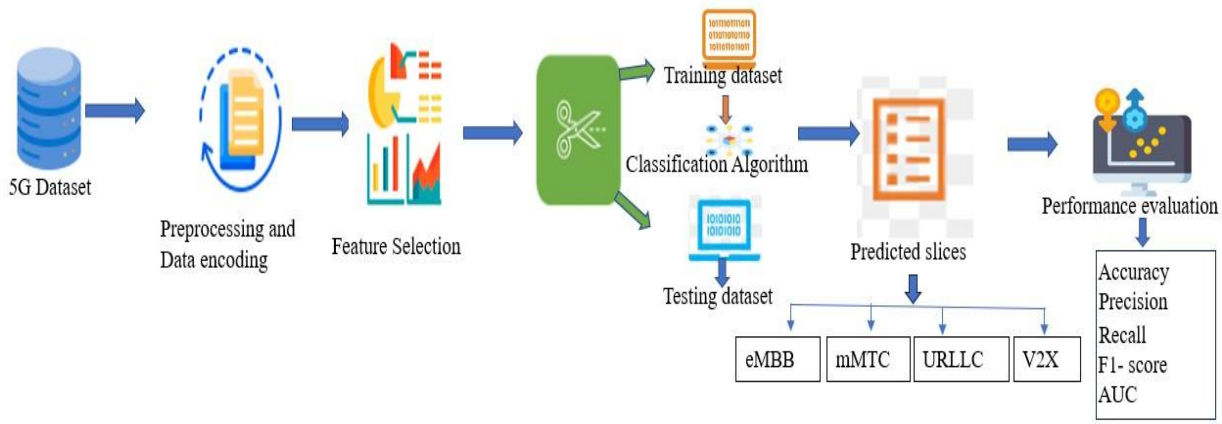

Figure 3.1: Architecture of the proposed model

Methodology

This study employed a publicly available dataset on 5G network slicing, consisting of 3,000 records designed to represent diverse service requirements in next-generation mobile networks [1]. The dataset includes three primary slice types: enhanced Mobile Broadband (eMBB), massive Machine-Type Communications (mMTC), and Ultra-Reliable Low-Latency Communications (URLLC). These categories were selected to capture the spectrum of use cases and performance demands within the 5G ecosystem. Moreover, the dataset incorporates details on the number of connected devices, providing insight into communication density across the infrastructure. At preprocessing, where the dataset is cleaned, reclassified by identifying slice-specific attributes and value ranges from the original data, and expanded by incorporating V2X parameters from literature, followed by feature encoding to establish four distinct slice categories (eMBB, mMTC, URLLC, and V2X); subsequently, feature selection is performed using statistical or model-based techniques to remove irrelevant attributes, after which the dataset is split into 70% for training and 30% for testing, and machine learning algorithms such as Random Forest and Gradient Boosting are applied to learn slice patterns, enabling the prediction of the four slice types, with model performance finally evaluated using Accuracy, Precision, Recall, F1-score, and AUC.

Result and discussion

This section presents the performance evaluation of the developed machine learning models using the 70/30 Train-Test Split approach on the extended dataset. The analysis focuses on assessing the classification capability of the models across the four defined 5G slice categories: eMBB, mMTC, URLLC, and V2X. Key performance metrics such as Accuracy, Precision, Recall, F1-score, and AUC are used to provide a comprehensive insight into the predictive effectiveness and generalization ability of each model. The results are summarized in Table 4.1, which highlights the comparative performance of the Random Forest and Gradient Boosting classifiers. Table 4.1: Train test split analysis of the extended dataset

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-score**	**AUC**
Random Forest	0.987	0.988	0.983	0.985	0.999
Gradient Boosting	0.986	0.986	0.983	0.984	1.000

Table 4.1, the Random Forest model displays outstanding performance on the testing dataset following the Train-Test Split, showcasing its ability to generalize well to new, unseen data. With an accuracy of 0.987%, the model accurately predicts the class for a substantial majority of instances. Notably, the precision of 0.988% indicates a low false positive rate. The model's high recall of 0.982% further emphasizes its proficiency in capturing a substantial portion of actual positive instances. The balanced F1-Score of 0.985% signifies a harmonious trade-off between precision and recall, ensuring a well-rounded performance. Additionally, the Area Under the ROC Curve (AUC) attaining 0.999% highlights the model's exceptional discriminative power.

Moreover, illustrated in the accompanying figure 4.1, we offer an exhaustive performance analysis of the extended dataset, specifically focusing on the train-test split results for both the Random Forest and Gradient boosting. This visual representation emphasizes the varied performance metrics, effectively showcasing the evaluation outcomes of these assessed algorithms on the specified dataset.

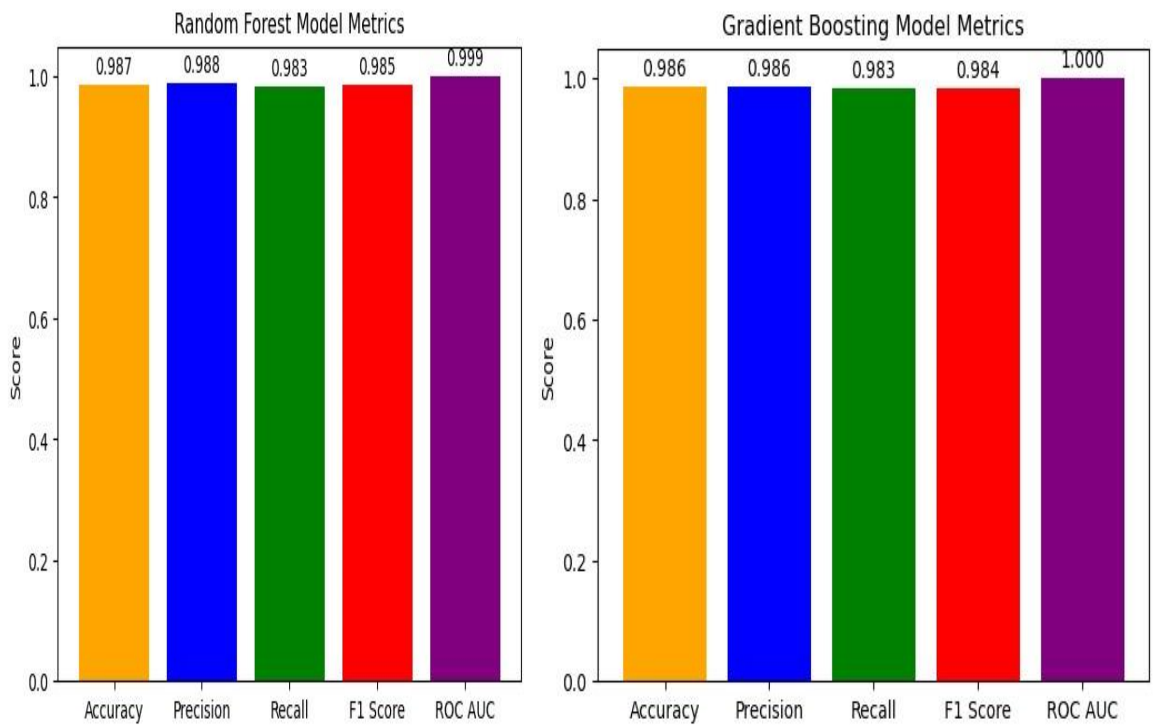

Figure 4.1: Train test split performance analysis of the extended dataset.

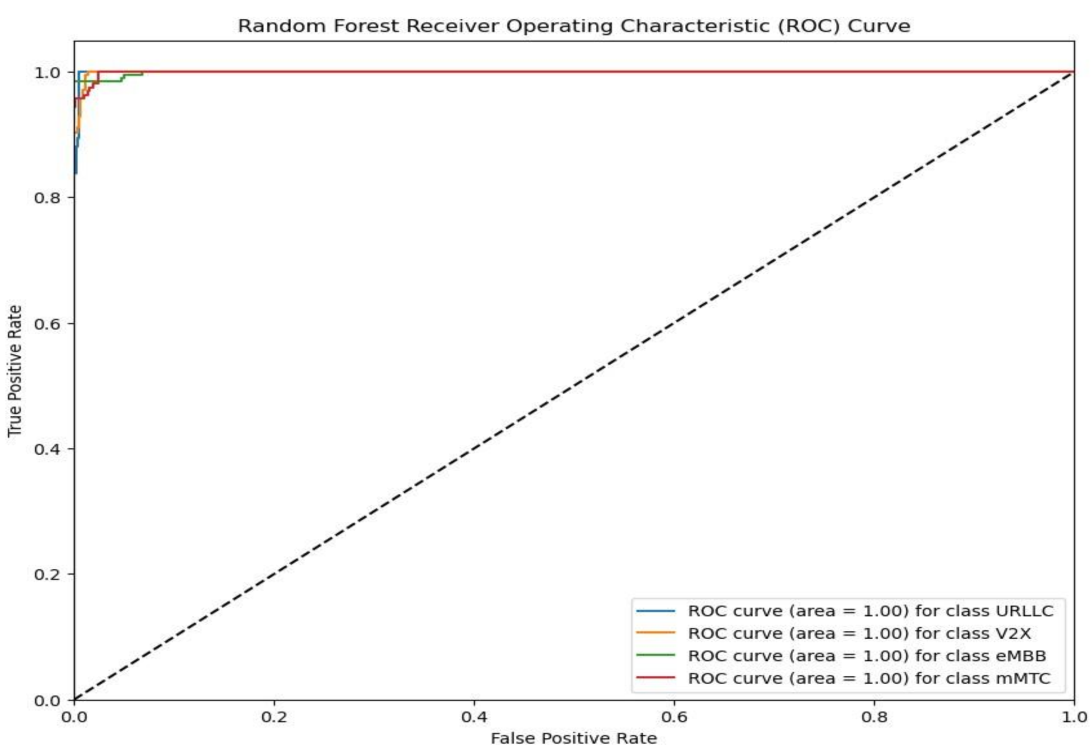

Figure 4.2: Random Forest ROC curve performance analysis.

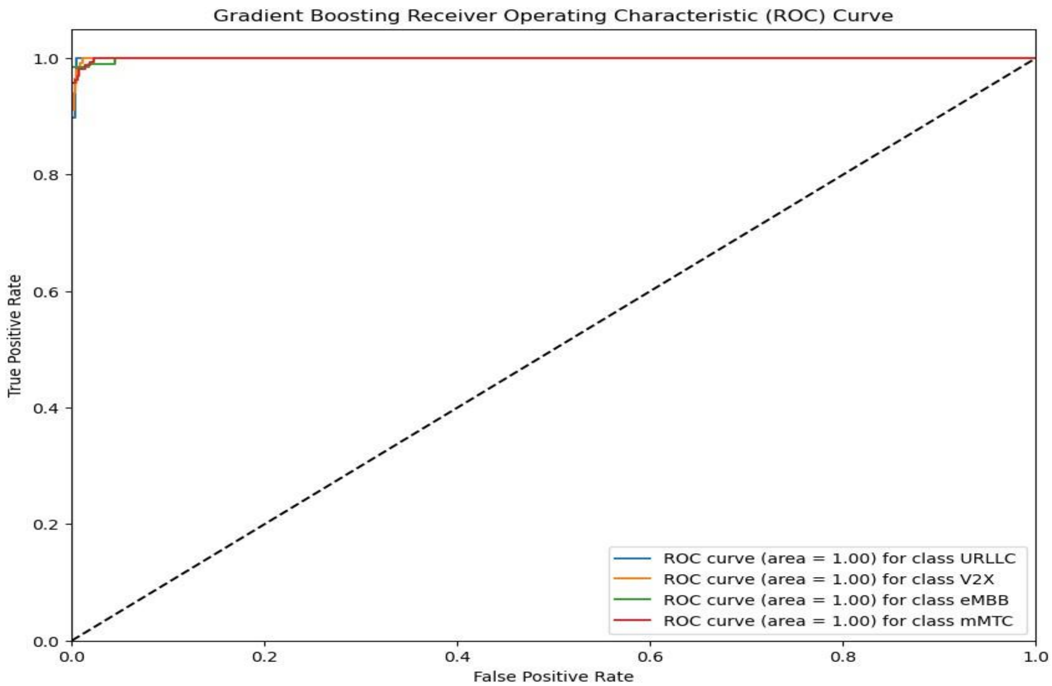

Figure 4.3: Gradient Boosting ROC curve performance analysis.

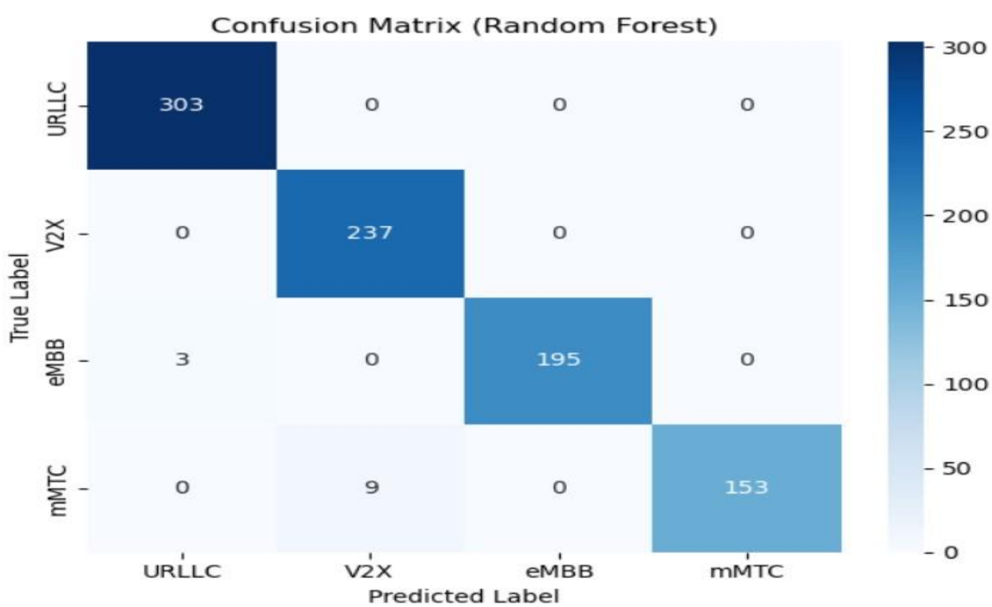

Figure 4.4: Confusion Matrix of Random Forest Classifier

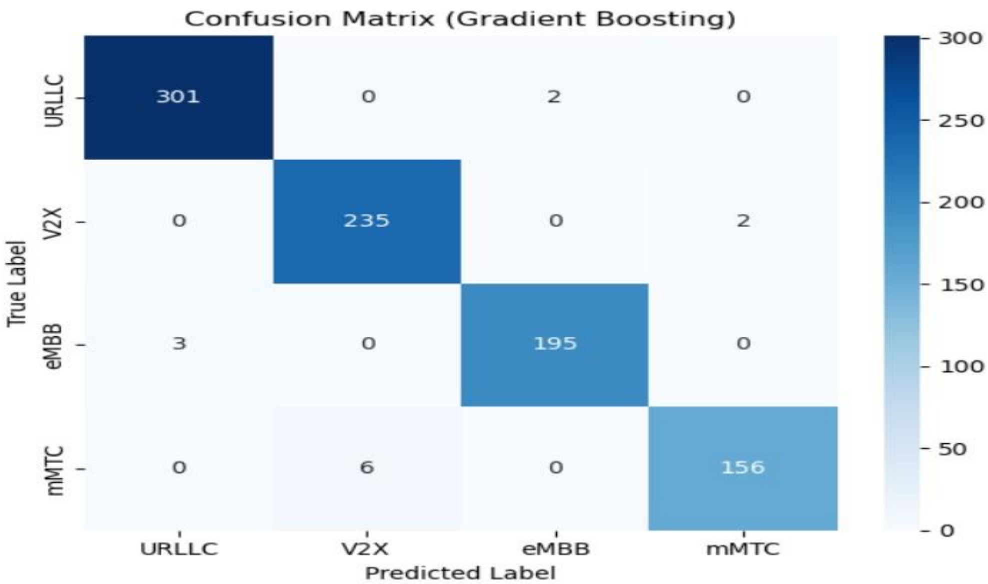

Figure 4.5: Confusion Matrix of Gradient Boosting Classifier

Conclusion

This study demonstrated the potential of ensemble machine learning techniques for accurate 5G network slice classification, focusing on the four key service categories: eMBB, mMTC, URLLC, and V2X. The strong performance of the Random Forest and Gradient Boosting models confirms their capability to handle complex slice differentiation and support intelligent network decisionmaking. These findings highlight the relevance of data-driven approaches in enhancing Quality of Service (QoS) and ensuring efficient slice allocation in modern communication networks. Looking ahead, future work will explore real-time implementation and the use of deep and reinforcement learning methods to enable adaptive and predictive slice management. Extending the approach to large-scale datasets and dynamic traffic environments will further validate its applicability in nextgeneration 5G and 6G systems. Overall, this research provides a solid foundation for the advancement of intelligent, automated network slicing frameworks.

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