Network Slicing for Beyond 5G Networks using Machine Learning

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***Abstract*—This paper explores the application of machine learning for practical applications in the context of Beyond 5G (B5G) communications. A variety of machine learning techniques, including neural networks, was applied on a labeled dataset about network slicing. Neural network models demonstrate superior performance in optimizing virtual network slices, crucial for enhancing Internet of Things (IoT) connectivity and efficiency. The findings can assist telecommunications professionals and policymakers, offering practical perspectives on AI technologies that can be applied in B5G scenarios for large communications networks.**

***Index Terms*—neural networks, network slicing, 6G communications, IoT communications, beyond 5G**

I. INTRODUCTION

This paper investigates possible applications of Artificial Intelligence (AI) for resource management procedures for Beyond 5G (B5G) networks. It highlights the complex nature of B5G networks and demonstrates how AI-driven solutions, leveraging neural network techniques, enhance efficiency and adaptability in resource allocation. Additionally, the study emphasizes the critical role of intelligent resource management in femtocell-based communications and Cloud-RAN environments. Big data applications assume larger throughput and speeds from the transmission network [Iqbal et al., 2020a], [Iqbal et al., 2020b]. Network slicing has the potential to customize network capabilities for specific requirements, particularly in the context of highly-connected networks and Internet of Things (IoT) applications. This automation is a crucial factor in enhancing network capacity and coverage, particularly benefiting IoT devices with constant connectivity and high data throughput needs, such as those used in smart cities and health monitoring systems.

The upcoming sixth-generation wireless technology, 6G [Latva-aho and Leppänen, 2019], is currently under development, aiming to succeed 5G. Expected characteristics include ultra-wideband and ultra-low latency communication with a target of one microsecond latency, significantly higher data rates, improved network reliability and accuracy, a pivotal role for AI in infrastructure and optimization, a human-centric focus with enhanced security and privacy features [Wahid et al., 2018], energy efficiency considerations [Qureshi et al., 2017], support for diverse applications beyond current mobile use scenarios (such as Internet of Things), and the adoption of flexible decentralized business models by mobile network operators [Letaief et al., 2019], [Docomo, 2020], [Tataria et al., 2021], [Alsharif et al., 2020]. The first 6G Wireless Summit was held in Levi, Finland in 2019 [University of Oulu, 2019] and the deployment of 6G systems is expected by 2028, although universally accepted standards defining its components do not yet exist.

AI is poised to play a pivotal role in the evolution of 6G technology, offering a range of transformative applications [Shi et al., 2023], [Yang et al., 2020], [Guo, 2020]. AI and communications convergence is expected to bridge the gap between digital and physical realms, introducing novel sensory experiences for users [Ji et al., 2021]. Intelligent IoT is another facet, suggesting that IoT devices in 6G will not only connect but also possess learning and decision-making capabilities. AI is anticipated to be integrated into networking equipment, empowering networks to autonomously learn and manage themselves, potentially reducing operational costs. Although an evolving field, various AI methodologies have been investigated for the advancement of B5G networks. Several deep neural networks (DNN) have been proposed for the optimization of 6G communication networks. [She et al., 2020] proposed a DNN multi-level architecture that enables device intelligence, edge intelligence, and cloud intelligence for URLLC. Additionally, DNNs can assist transmission impairement mitigation [Maniak et al., 2022]. [Wang et al., 2021] has investigated the process of designing robust deep learning models that can be deployed on resource-constrained IoT devices. Furthermore, dynamic DNN have been proposed in order to automatically optimized network parameters according to device usage [Ma et al., 2022]. Deep learning [Zhai et al., 2022] and graph-based [Wang et al., 2022] approaches have been used for location optimization of UAV device networks. Finally, edge computing on interconnected devices has been investigated as a base for federated learning [Sirohi et al., 2023].

Cellular communications and the impending deployment of 5G mobile networks demand strict adherence to high-reliability standards, ultra-low latency, increased capacity, enhanced security, and rapid user connectivity, with a focus on sustainability [Lv et al., 2018]. Mobile operators are actively seeking programmable solutions that allow for the concurrent accommodation of multiple independent nodes on the same physical infrastructure. The advent of 5G networks introduces Network Slicing (NS) as a pivotal capability, facilitating the partitioning of the network into distinct virtual slices [Khan et al., 2020]. Each network slice caters to specific needs, allowing diverse services like smart parking meters and driverless cars to coexist with tailored resource allocation, rendering the one-size-fits-all service delivery approach obsolete. Three example slices are the Mobile Broadband (eMBB), the Ultra-Reliable Low Latency Communication (URLLC) and the Massive Machine Type Communication (mMTC) slice [Thantharate et al., 2020]. The eMBB refers to data-heavy operation with high-bandwidth and high-speed data transmission, for activities such as video streaming and online gaming. URLLC provides stability and low-latency for applications such as autonomous vehicles and industrial automation [Ahmed et al., 2022], [Hijji et al., 2023]. On the other hand, mMTC supports large, multi-node IoT device and sensor networks. In the realm of 5G and 6G, network slicing facilitates the customization of network services to cater to specific use cases, guaranteeing optimal performance, efficient resource utilization, and enhanced user experiences aligned with the distinct requirements of applications like eMBB, URLLC, and mMTC.

The paper introduces a novel approach to virtual resource management within intricate B5G networks, leveraging ML/AI algorithms for the dynamic allocation of resources based on real-time network conditions, traffic patterns, and user demands. This includes the goal of automating network slicing using AI-based algorithms. This research not only contributes to the progression of B5G technologies but also showcases the practical application of AI in achieving intelligent resource management and optimization. The findings are expected to significantly influence future innovations in B5G and beyond.

II. METHODS AND MATERIALS

A. Data Sources

The 'Network Slicing' dataset utilized in this research originates from the CRAWDAD project [Thantharate et al., 2022]. The dataset encompasses a comprehensive set of observations, comprising 466,739 instances and 8 feature columns. The features are 'Use Case Type', 'LTE/5G UE Category', 'Technology Supported', 'Day', 'Time', 'QCI' (Quality of Service Class Identifier), 'Packet Loss Rate', and 'Packet Delay Budget'. The dataset's primary objective is to investigate and model various aspects of B5G converged Optical Wireless Networks, with a specific focus on deep-slice scenarios. The histograms of the values for the different input features are shown in Figure 1. The 'Slice Type' column serves as the target variable, indicating the classification of network slices into three distinct classes eMBB, URLLC and mMTC. Categorical variables were converted to integers using one-hot encoding. In order to solve a non-trivial problem, the 'Use Case Type' column was ignored. The end task was the classification of a device to the appropriate slice type, considering an unknown use case.

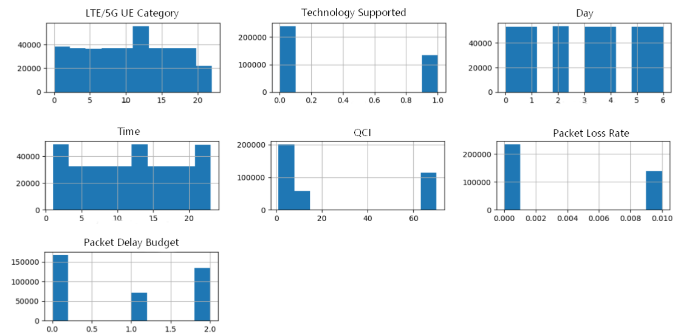

Fig. 1: Histograms of the values for the Network Slicing Dataset.

B. Experiment

In order to facilitate experimentation, the dataset was split in two separate train and test subsets with a 20% ratio. An additional 20% of the train data was held out for model validation during training. The split was applied in a stratified manner, in order to preserve class distribution of the output labels.

For the network slicing dataset, a Support Vector Machine (SVM), a Random Forest Classifier (RFC) and a Fully Connected Neural Network (FCNN) were employed to predict the target network slice based on the input features. Exploratory analysis was performed to identify the characteristics of the datasets. A random forest model was used to assess feature importance within the train dataset.

The investigated methodologies are staple methods in machine learning, used in various domains and applications [Boateng et al., 2020], [Ren et al., 2016]. A Support Vector Machine (SVM) is a supervised machine learning algorithm which finds the hyperplane that best separates the data into different classes while maximizing the margin between classes. SVM is effective in high-dimensional spaces and is particularly useful when the data has clear separations between classes. A Random Forest Classifier (RFC) is an ensemble learning method that builds diverse decision trees using random subsets of the data and features, and then combines their predictions to improve accuracy and generalization. Random Forests are robust, handle high-dimensional data well, and are less prone to overfitting compared to individual decision trees. A Fully Connected Neural Network (FCNN) is a type of artificial neural network architecture where each node in one layer is connected to every node in the subsequent layer. This architecture allows for complex learning and representation of patterns in data. As baselines, logistic regression (LR) and Gaussian Naive Bayes (GaussianNB) were also used.

In this experiment, the following models were used:

- LR with an L2 penalty score and lbfgs solver,
- GaussianNB with a 1e-9 smoothing term,
- an SVM with Radial Basis Function (RBF) kernel,
- a RFC with 100 estimators and Gini criterion, and
- a FCNN with 3 FC layers and a total of 167 trainable parameters.

III. RESULTS

In this study, two independent experiments were performed, in order to demonstrate the effectiveness of AI approaches for B5G-related applications. The first experiment targeted the classification of the optimal virtual network slice depending on the usage characteristics of a device. The second experiment targeted the identification of proposed locations for a small cell node deployment based on the existing network of small cells.

For the network slicing dataset, three different machine learning models were employed: SVM, RFC and FCNN. Initially, exploratory analysis was performed on the network slicing dataset. Figure 2 visually represents the importances of input features obtained through random forest impurity analysis on the Network Slicing dataset. The impurity-based analysis conducted by the random forest model is a method to assess the contribution of each feature to the predictive accuracy of the model. Higher importance scores suggest that the corresponding features play a more crucial role in the model's decision-making process. This information is valuable for understanding which features have a more substantial impact on the model's ability to discriminate and classify different instances in the dataset. Packet-related features, namely packet loss rate and delay budge demonstrated the highest importance. Supported technology also plays an important role. Day, time and quality features do not have a large influence.

The results of classification of the inputs to the optimal network slice are shown in Table I. The FC neural network showed considerably improved performance, with 97.88% testing accuracy, in classifying the input sample to each of the eMMB, URLLC and mMTC slices. This indicates that Neural Network approaches, even with simple networks, can be used to automatically determine the optimal slice for the usage characteristics of a connected device. The lower performance of LR and GaussianNB in this context could be attributed to their simplicity and limitations in handling the high dimensionality of complex network data. In complex network scenarios, patterns and nonlinear relationships are better captured by more sophisticated models like neural networks, as also demonstrated by the experimental results.

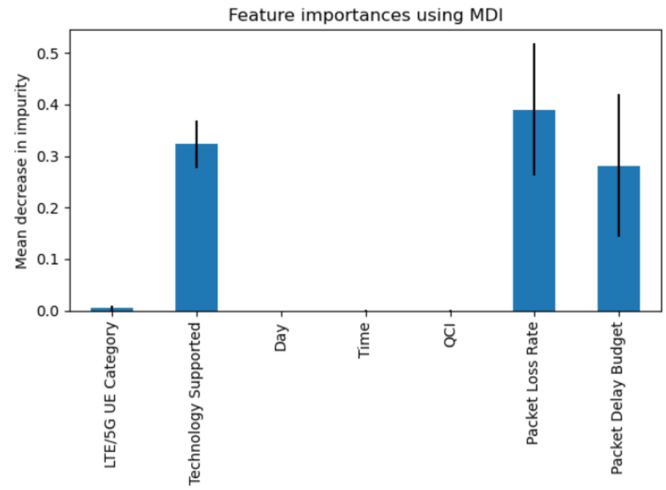

Fig. 2: Importances of the input features based on random forest impurity analysis.

TABLE I: Table Type Styles

Model	**Train Acc (%)**	**Test Acc (%)**
LR	67.79	67.83
GaussianNB	55.15	55.16
RFC	90.99	91.16
SVM	92.21	92.19
FCNN	98.43	97.88

IV. DISCUSSION

In this study, we conducted experiments to demonstrate AI's effectiveness in B5G applications, focusing on classifying optimal virtual network slices based on device usage characteristics. Three machine learning models (SVM, RFC, FCNN) were used, with the FC neural network outperforming, highlighting neural network effectiveness. While promising, limitations include the need for generalization to diverse real-world scenarios, limited model optimization, and potential dataset biases impacting broader context applicability.

The results underscore diverse machine learning methodologies' applicability in structured B5G data, with varying effectiveness. Neural network models showed superior performance, but their "black-box" nature raises interpretability concerns. Static datasets may not fully emulate dynamic B5G networks, impacting adaptability and scalability. Future research should address interpretability, dataset diversity, and AI robustness. Evaluating models in real-world deployments and exploring ensemble or hybrid models could enhance practical utility, contributing to resilient, efficient, and interpretable AI solutions for B5G technologies. The study's relevance extends to telecom professionals, network engineers, architects, and policymakers, offering insights into AI's impact on B5G network performance.

V. CONCLUSION

In summary, this research showcases progress in resource management techniques for B5G networks, emphasizing the integration of AI into virtual resource management. Traditional AI methodologies, such as SVM and FCNN, were applied on a labeled dataset to optimize network slicing. The outcomes highlight the superior performance of neural network approaches. The consistent efficacy of neural network models underscores the potential of AI to adeptly address the inherent complexities of advanced network systems. These advancements directly enhance network capabilities for highly connected information systems by bolstering flexibility and efficiency. Subsequent research efforts should focus on addressing recognized limitations, delving into ensemble models, and evaluating real-world deployment scenarios. The practical implications derived from the study provide insights for professionals within the telecommunications sector, elucidating the concrete application of AI in B5G scenarios.

ACKNOWLEDGEMENTS

This work was carried out during project "EXperimentation and simulation based PLatform for beyond 5G Optical-wireless network Research and development" (EXPLOR, Grant agreement ID: 872897), supported by the European Union. For the purpose of Open Access, the authors have applied a Creative Commons Attribution (CC BY) license to any Author Accepted Manuscript (AAM) version arising from this submission.

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