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A FUTURE TREND ON 5G NETWORK SUB-SLICING TECHNIQUES FOR MACHINE LEARNING ALGORITHMS

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ABSTRACT

One of the primary objectives of 5G networks is to meet the need for vertical services. Artificial reality/virtual reality, electronic health records, live video streaming, robotics, driverless vehicles, and many other applications might benefit from 5G networks. Optimal 5G Network Sub-Slicing Automation (ONSSA) is a novel machine learning framework introduced in this paper for autonomous and dynamic 5G network slice processing. After analyzing historical data and the present state of the network, the framework uses the LazyPredict module to automatically choose the most effective unsupervised learning algorithms. For systems that run concurrently at numerous infrastructure layer levels, network slicing poses very difficult and critical security challenges. Some security challenges that need attention are as follows: It is possible to implement security-based interslice, interslice, and multidomain. The data is vulnerable to hacking in situations when a conventional network based on machine learning is used. Accordingly, Data Communication Network as a Service (DCNaaS), is a whole new service model for Mobile Network Organizations (MNOs). To evaluate the framework, we used Python for dynamic testing and Anaconda Spyder for machine learning implementation. To address the slice allocation problem, this research makes use of datasets and machine learning techniques. We have evaluated the slice allocation approach using many ML models. We demonstrated in the simulation that the proposed method correctly allocates the best slice for service.

Keywords: *5G Networks, Optimal 5G Network Sub-Slicing Automation, Lazypredict, Mobile Network Organizations, Data Communication Network As a Service, Machine Learning*

1. INTRODUCTION

Machine learning enables new solutions to challenging issues, enhanced 5G network slicing and orchestration, and unexplored network optimization opportunities. Fifth-generation (5G) cellular networks, which promise to provide previously unheard-of data speeds, service quality, connectivity, and network flexibility, are poised to transform mobile broadband communication [1].

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Network slicing, a novel approach to mobile broadband communications, enables the development of end-to-end virtual verticals that share the physical infrastructure [2]. We often use quality of service (QoS) and quality of experience (QoE) measurements to assess mobile communications systems, including 5G [3]. While Quality of Experience (QoE) measures specific service, Quality of Service (QoS) is the total of all the characteristics of a telecom service that influence its ability to meet the demands of consumers. Using solely QoS indications, it offers a method for calculating QoE parameters [4, 5].

5G network slicing is made possible by software-defined networking, cloud computing, and network service virtualization. By adopting a network-slicing architecture, it is feasible to provide adaptable solutions for a variety of business scenarios and groups of network traffic that share networks [6]. Network slicing makes it feasible to build several 5G networks with comparable topologies, each with a unique set of functionalities and performance levels. The multiple services provided by network slicing technology might be advantageous for a variety of industries, including voice communication, intelligent transportation systems, healthcare, and many more. Figure 1 shows a diagram of the network slicing procedure. When discussing virtual networks, the term "network slicing" refers to a method of connecting several virtual networks to a single physical infrastructure [7].

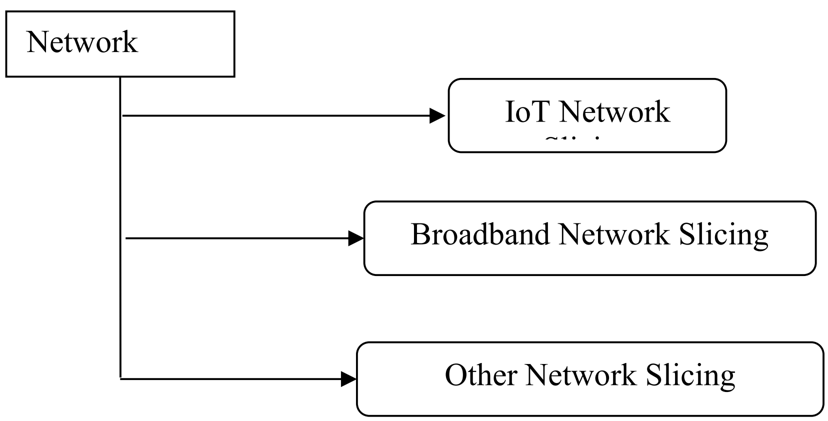

Figure 1: Function of 5G Network Slicing

In this study, we explore the use of computational tools for slice categorization to aid in decision-making, and we provide an ideal optimal 5G Network Sub-Slicing Automation system. Several 5G network use cases are presented in this article based on factors including throughput, availability, reliability, and latency. The network slicing system model is shown here. We simulated the dataset using several machine learning-based methods and evaluated how well they performed.

The primary objective was to validate, situation-specifically, the shared features of these methods and their implementations in the slice classification and selection processes. Then, the framework that provides the best experience for the user was proposed. We opted for a hybrid strategy that combined machine learning (ML) with the K-means clustering technique to build and manage the Mobile Network Organizations (MNO) service in heterogeneous mobile network situations where many domains were sliced. To ensure the framework was valid, testbeds were used to map the key Quality of Service (QoS) requirements.

Recent advancements in 5G network architectures have increasingly focused on network slicing as a means to support diverse application requirements across vertical industries. However, current literature primarily addresses slicing at a coarse level, often neglecting the granularity needed for optimizing resource allocation in machine learning (ML)-driven services. Existing sub-slicing frameworks are either static, lack scalability, or fail to dynamically adapt to the real-time demands of ML algorithms, particularly those with heterogeneous latency, bandwidth, and reliability needs. This study introduces a novel sub-slicing methodology that bridges this gap by leveraging intelligent decision-making processes tailored specifically for ML workloads. By aligning network resource provisioning with the contextual demands of varied ML models, our approach not only enhances service quality but also improves overall

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network efficiency. In contrast to existing methods, this work integrates adaptive learning mechanisms and real-time analytics to inform sub-slicing, marking a significant step forward in aligning 5G capabilities with the dynamic requirements of emerging AI-driven applications.

1.1. Contribution

- The need for effective network slicing in 5G networks, especially for applications requiring low latency. The top networking layers, which include queuing, processing, and access delays, include stochastic delays that make it difficult for traditional techniques to deliver low-latency communication (LLC).
- To properly deliver LLC services, these obstacles must be overcome, even if the transmission delay only accounts for a tiny percentage of the end-to-end latency.
- Application of a model for slice selection using a combination of machine learning and multicriteria decision-making techniques
- During network execution, decision matrices are created using data analytics tools that specify acquisition and characterization models of network datasets.
- Creating embedded software for mobile devices with many streams that allows users to choose slices.
- The Optimal 5G Network Sub-Slicing Automation (ONSSA) is a novel machine learning framework and also introduce new techniques for Data Communication Network as a Service (DCNaaS), is a new service model for Mobile Network Organizations (MNOs).
- To classify the result is performed the some machine learning algorithms like: CAT Boost, XGBoost, Random Forest and Logistic Regression.
- The major findings is 5G communication security level is low, my side improved the security problems some new methods are used.

2. RELATED WORKS

Researchers are investigating several methodologies and tactics to ascertain the appropriate orchestration of 5G network slices. Key topics in our analysis of the current state of the art include 5G network slicing and the use of machine learning for optimizing 5G network slices.

End-to-end network slicing, which facilitates the creation of many logical virtual network slices with a shared physical infrastructure, is an essential component of 5G networks. End-to-end network slicing, which facilitates the creation of many logical virtual network slices with a shared physical infrastructure, is an essential component of 5G networks. The investigation determined that cloud computing and virtualization are the technologies enabling the feasibility of 5G networks, software-defined networking (SDN), and network function virtualization (NFV) [8]. A thorough analysis of 5G network slicing that examines both the advantages and disadvantages of 5G enabling technologies [9]. By combining software-defined networking (SDN) with network function virtualization (NFV), a technique was suggested for efficiently building and managing 5G network slices. It was emphasized that automation was necessary for optimal network slice orchestration. Softwarization in 5G and 5G network slicing were among the many ideas, technologies, and solutions that were researched and studied [10].

Long short-term memory (LSTM) networks were used in research to predict the needs of mobile traffic in 5G networks. It was possible to evaluate the effectiveness of LSTM models using datasets that represented real mobile traffic [11]. The simulation results of the paper show that LSTM beats more conventional time series forecasting models like ARIMA. In another work aiming at using traffic prediction models to actively distribute network resources in sliced networks, a deep learning-based strategy was also suggested [12].

The study in [13, 14] suggested an order preference strategy based on NSSF, which was motivated by TOPSIS (similarity to ideal solution). A mobile user or terminal may choose from many connection options according to network division principles, taking into account slicing performance factors, service needs, and user preferences. From the ABC idea to 5G and beyond in the realm of mobile technology, NSSF is seen as the next natural step. One way to think about NSSF is as an MCDM issue, which investigates the possibility of categorizing the available slices according to their weights and characteristics. Based on TOPSIS, it was created. Top-down reasoning, computational logic, and mathematical structure make TOPSIS a popular decision-making tool. However, since rank reversibility occurs, the outcomes are uncertain.

In Internet of Things (IoT) contexts, [15] proposed a method for selecting 5G network slices. By use of Edge Computing resources, hybrid machine learning techniques, and MCDM approaches, it eventually helps consumers by enhancing data processing and routing for Internet of Things applications. Based on the outcomes, both the suggested solution and the MCDM approaches used proved to be very successful. This shows how incredibly flexible the suggested ordering of the many approaches is about the chosen weights.

The proposed dynamic slice selection approach entails mapping the current slice to the next and assessing the situation. Consistent identification and autonomous attractor generation were obtained using the Dirichlet Process Mixture Model (DPMM) and the Bayesian Attractor Model (BAM). Additionally, taught automatically via feedback was situational mapping. In the framework of video streaming, dynamic slice selection was used; the findings reveal that the suggested approach can lower slice changes while preserving a decent degree of video streaming quality [16].

The study offers a thorough overview of many industry efforts and activities connected that SDN and NFV are widely used to speed up 5G network slicing. Regarding practical implementation, technological acceptance, and deployment strategy, the report evaluates many 5G architectural solutions. The writers also stress the attempts at standardizing as well as the scene of 5G network slicing and network softwarizing seen from both academic and commercial angles [17].

An end-to-end network slicing testbed for 4G/5G systems is presented, using cloud-based SDN and NFV. Modern SDN and NFV technologies are used here to provide a programmable, flexible network architecture that can be customized and optimized. Employing their testbed design, implementation, and assessment using numerous use cases, the authors highlight the scalability and performance of the network slicing system [18].

This addresses the natural constraints of the conventional K-Means method, including its sensitivity to beginning circumstances and the need to manually choose the number of clusters, and generates end clustering results that are both clear and simple to read. A real IoT dataset test of our method revealed that our pipeline can effectively categorize the data into three separate categories. These cluster traits are easy to grasp and connected to different kinds of network slices in the 5G network, thereby showing how well our method manages the complexity of IoT traffic for 5G network slice allocation [19].

The suggested convolutional neural networks-long short-term memory technology demonstrates superiority over traditional machine learning techniques, indicating promise for real-time threat detection. An assessment of the suggested system using a 5G dataset demonstrates an outstanding accuracy of 99%, exceeding prior research and validating the method's effectiveness. Moreover, network slicing markedly improves quality of service by categorizing services according to capacity. Future research will focus on practical applications, including the evaluation of diverse datasets and the assessment of the model's adaptability across different contexts [20].

Emphasizing C-RANs, this review paper offers a complete clarification of the most recent advances in DRL-based SAC. While stressing the key issues and possible research paths, the paper underlines the advantages of using Deep Reinforcement Learning (DRL) for Soft Actor-Critic (SAC), such as enhanced network performance and efficiency. Implementing these systems in actual situations, however, raises certain problems and trade-offs that must be carefully evaluated. More research and development are needed to solve these problems and guarantee the effective implementation of DRL-based SAC systems in wireless networks [21].

This article examines the research gap, prominent research challenges, and the practical implementation of key use cases enabled by network slicing. This is the first effort to impartially evaluate and provide a thorough analysis of the current advancements in network slicing resource management modules and notable industrial applications enabled by network slicing. This project aims to help researchers in developing creative ideas and to support network members in the implementation of network slices for industrial applications [22].

Everyone wants to present an overview of the security state of the network technologies employed by 5G and conduct a detailed investigation of carefully chosen papers deemed relevant. After investigating this, we discovered that although there are a lot of studies on threats, they are not rigorously structured and exhibit conceptual ambiguity that might mislead practitioners. In addition, the variety of defenses could be confusing to designers. In order to provide light on how to safeguard these networks, we have thoroughly examined the risks and solutions. From this vantage point, we suggest research avenues to enhance or expand existing defenses. Virtual networks exhibit systems, and a significant portion of system security theory is applicable to them, despite their unique features [23].

3. METHODOLOGY

There has been a lot of progress, but there is still a need for greater study and development into how to make the most effective use of a mobile network's limited physical resources. We want to make a difference with the machine learning solution we're proposing by integrating supervised learning for traffic prediction and proactive scaling with reinforcement learning for smart resource allocation and dynamic network slicing.

Among the many services that may coexist on a single infrastructure with fifth-generation networks are high-speed video streaming, vast Internet of Things connections, and ultra-reliable low-latency communications. This presents a difficulty in making dynamic resource allocation more challenging.

Real-time resource allocation is difficult given the unpredictable and surprising resource demands of competing services. These often shifting demands are too big for antiquated, time-consuming approaches such as static or manual allocation.

The escalating size and intricacy of 5G networks have made manual or rule-based methods outdated since they are unable to accommodate the network's dynamic needs. Machine learning can analyze previous data and current circumstances to forecast demand, distribute resources dynamically, and optimize network performance, necessitating a more sophisticated, automated methodology.

3.1. Dataset Description

Congestion and associated issues are a common source of anxiety among city dwellers. Transportation, building, and congestion management planning are just a few areas that might benefit from an understanding of traffic patterns and data analysis.

It is a fantastic resource for traffic analysis as it draws on data collected by a computer vision model. There are four vehicle kinds identified by the model: automobiles, trucks, buses, and motorcycles. Additional variables in the dataset include the following: time in hours, date, days of the week, and amounts of vehicle type (auto, bike, bus, and truck). The sum of all the car models found in that fifteen-minute time frame is shown in the "Total" column.

The dataset is updated every 15 minutes and provides detailed information on traffic patterns throughout the month. One column in the dataset defines the four traffic scenario classifications: heavy, high, normal, and low. We may use this information to track traffic patterns and congestion levels over the week. This information facilitates transportation planning, congestion management, and traffic flow analysis. It is useful for pinpointing problem areas with traffic, assessing demand for vehicles, and planning infrastructure upgrades. Targeted procedures, such as signal tuning and lane alterations, are made possible by the dataset. Hourly, daily, or date-specific traffic patterns may be examined, and researchers can look for links with external sources. It bolsters studies of transportation-related traffic patterns and vehicle connections. When making decisions on infrastructure and zoning, urban planners may take traffic into account.

Taken together, the dataset equips users with the knowledge they need to aid in the creation of greener and more efficient metropolitan areas, improve public transit, and base choices on empirical evidence. The speeds of the vehicles will be part of the data collection. In addition, rather than focusing on a single route, the information will handle a traffic intersection. The goal of this update is to improve traffic management analysis and decision-making by providing a more comprehensive picture of traffic dynamics. Transportation planning and congestion management projects will find the information more valuable with the inclusion of speed data; they will enhance comprehension of traffic flow and efficiency. The dataset was available at https://www.kaggle.com/datasets/hasibullahaman/traffic-prediction-dataset.

3.2. Monitoring of the Foundation and Technological Achievements

Our method introduces three significant technical advances in network orchestration: Optimal 5G Network Sub-Slicing Automation (ONSSA) architecture, the Data Communication Network as a Service (DCNaaS), and the Mobile Network Organizations (MNOs) paradigm.

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The proposed ONSSA architecture is based on the MNO pipeline to provide autonomous orchestration capability. When adjusting hyperparameters, the system employs Ultra Pitch, therefore users have very specific management of decisions for the distribution of resources. The addition of this makes the framework more able to react to changing network situations without compromising peak performance.

The introduction of the DCNaaS paradigm by the other contributions changes how commercial networks use 5G possibilities. This concept greatly enhances network service delivery by allowing businesses to use customized network slices free from the control of complicated infrastructure.

3.3. Optimal 5G Network Sub-Slicing Automation

By automatically distributing resources to various services in response to actual demand, optimal 5G network sub-slicing automation boosts network efficiency. Automation minimizes latency and maximizes throughput by utilizing artificial intelligence (AI), machine learning (ML), and orchestration frameworks. To maximize performance for uses like smart cities, industrial IoT, and autonomous vehicles, telecom providers can use this method to build customized sub-slices inside a larger 5G slice. Automated sub-slicing improves network resilience by adjusting resources in response to congestion predictions. Also, improving spectrum utilization and doing away with manual intervention, lowers operational costs. Additional enhancements to dependability and safety include self-healing systems and real-time monitoring. 5G networks are becoming more complicated as time goes on, automation streamlines management while preserving service-level agreements (SLAs). Using a combination of software-defined networking (SDN) and network function virtualization (NFV), sub-slicing automation guarantees scalability and flexibility, allowing for next-gen digital ecosystems to have efficient connectivity, ultra-reliable communications with low latency, and flexible infrastructure.

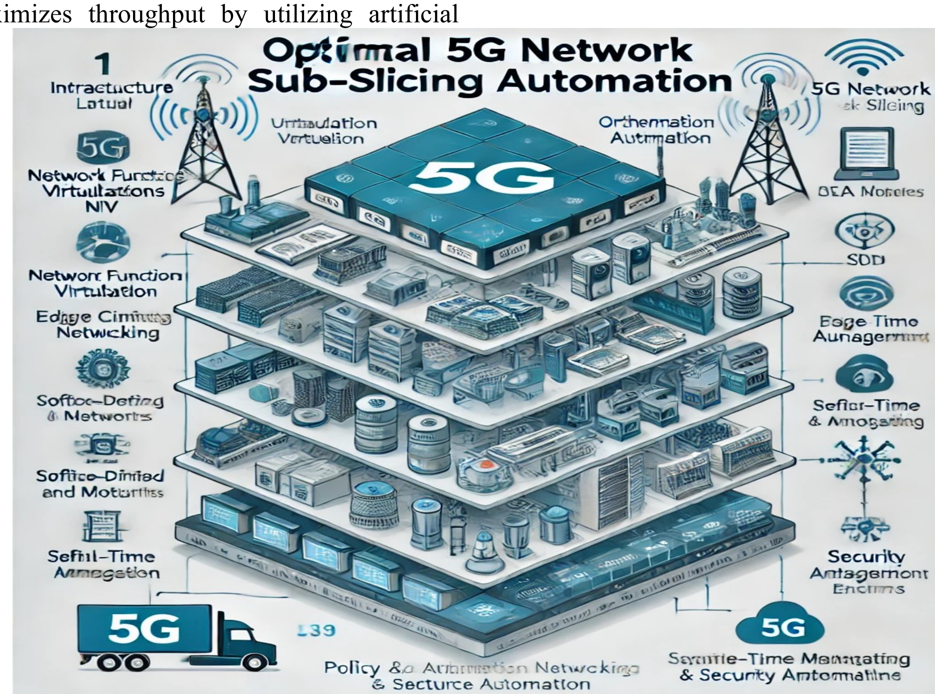

Figure 2: Optimal 5G Network Sub-Slicing Automation

The Optimal 5G Network Sub-Slicing Automation design shown in Figure 2 consists of many levels that provide effective resource allocation and network optimization. The Infrastructure Layer comprises physical network components such as 5G base stations, edge computing nodes, and cloud data centers, providing the basis for connection. The Virtualization Layer utilizes Network Function Virtualization (NFV) and Software-Defined Networking (SDN) to provide dynamic and adaptable network slicing. The Orchestration and Automation Layer incorporates

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AI-driven algorithms, machine learning, and real-time analytics to efficiently distribute resources and optimize sub-slices. The Service Management Layer supervises policy enforcement, SLA adherence, security, and real-time monitoring to guarantee uninterrupted operations. The User & Application Layer encompasses many consumer-facing uses, including the Internet of Things (IoT), smart cities, automated manufacturing, and driverless vehicles, all of which use ultra-reliable, low-latency 5G services. This stratified architecture enables telecommunications operators to automate network sub-slicing, guaranteeing scalability, efficiency, and uninterrupted service delivery across diverse applications.

3.4. Data Communication Network as a Service

Data Communication Network as a Service (DCNaaS) is a cloud-based framework that offers scalable, on-demand network infrastructure for efficient data transfer. It allows enterprises to use networking resources without capital expenditure on physical infrastructure, hence decreasing costs and improving flexibility. By using technologies like Software-Defined Networking (SDN) and Network Function Virtualization (NFV), DCNaaS guarantees effective traffic management, adaptive bandwidth allocation, and enhanced connection. Organizations get advantages from improved security, instantaneous monitoring, and automatic network modifications in response to demand variations. DCNaaS provides low-latency, high-speed connectivity for applications such as IoT, AI, and business collaboration via multi-cloud integration and edge computing enablement. The pay-as-you-go concept improves operational efficiency, enabling organizations to adjust resources based on business requirements. Moreover, DCNaaS providers guarantee adherence to industry standards by providing encryption, firewalls, and intrusion detection for safe communication. With the rapid advancement of digital transformation, DCNaaS is transforming connections by providing flexible, intelligent, and economical networking solutions for organizations globally.

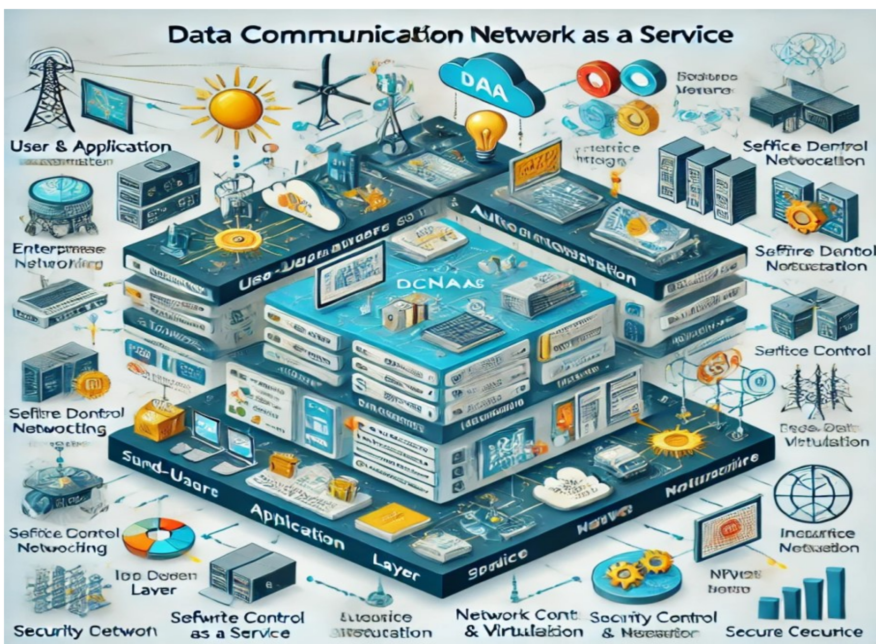

Figure 3: Data Communication Network as a Service

Figure 3 for Data Communication Network as a Service (DCNaaS) has numerous levels, each essential for facilitating efficient, scalable, and secure data Communication.

- **User & Application Layer:** Interacting with the network includes end-users, corporate apps, Internet of Things devices, and cloud services, all shown by this block. This category encompasses all devices that need the smooth transfer of data, including sensors, industrial controls, cell phones, and AI-driven tasks.

- **Service Orchestration Layer:** Automation of the network, enforcement of policies, and real-time analytics are all handled by this layer. It guarantees that, depending on user demand and network circumstances, resources are allocated dynamically. Automated tasks powered by AI enhance network performance without compromising service-level agreements (SLAs).
- **Network Control & Virtualization Layer:** The scalability and adaptability of this block are provided by the Software-Defined Networking (SDN) and Network Function Virtualization (NFV) components. The combination of software-defined networking (SDN) with NFV allows for centralized network administration and the efficient and quick deployment of virtualized services instead of hardware-based network operations.
- **Infrastructure Layer:** The infrastructure for the backbone network, edge computing nodes, and cloud data centers make up this section. Computing near the network's periphery, or "edge," lowers latency compared to data processing in distant cloud data centers. For reliable, high-speed data transmission, the backbone network links all the various parts.
- **Security & Compliance Module:** Security log analysis, intrusion detection, firewalls, and encryption are all part of this section. Compliance with industry standards, prevention of cyber risks, and protection of data integrity are all achieved via these processes. To prevent unwanted parties from gaining access to any network transaction, security frameworks are put in place.

3.5. Mobile network organizations

Deploying and administering 5G communication is a critical function of mobile network organizations (MNOs). MNOs provide low-latency services, high-speed data transfer, and seamless connection. Network slicing, edge computing, and 5G technologies include massive MIMO and others that MNOs are using to create scalable and very dependable networks. Organizations like these use SDN and NFV to make their networks more adaptable, make better use of their resources, and cut down on operating expenses. With 5G, MNOs can power cutting-edge apps like smart cities, autonomous cars, IoT ecosystems, and immersive virtual reality and augmented reality experiences. The quality of service is further improved by AI-driven network automation, which also improves predictive maintenance and real-time traffic management. To keep user data secure, MNOs continue to prioritize security protocols for network intrusion prevention, end-to-end encryption, and related technologies. With the increasing use of 5G, mobile network companies are spearheading digital transformation, providing businesses and consumers with wireless communication networks that are quicker, more efficient, and more dependable.

Below Figure 4 three primary components of a Mobile Network Organization (MNO) block diagram are the Core Network, the Radio Access Network (RAN), and the User and Application layer.

- **Core Network Block:** This block includes the 5G Core (5GC), Software-Defined Networking (SDN), and Network Function Virtualization (NFV) to manage traffic and ensure seamless connectivity. The core network is responsible for data routing, authentication, mobility management, and enabling ultra-reliable low-latency communication (URLLC).
- **Radio Access Network (RAN) Block:** All the components necessary for seamless wireless communication are housed in this block: 5G base stations, edge computing nodes, and massive MIMO antennas. RAN ensures efficient spectrum utilization and lower latency by connecting user devices to the core network and improving performance through beamforming and network slicing.
- **User & Application Block:** Included in this category are 5G-dependent end-user devices, Internet of Things apps, autonomous cars, and smart city services. It stands for the practical uses of MNOs' hyper-low latency, very fast data transfers, and enormous machine-type communications.

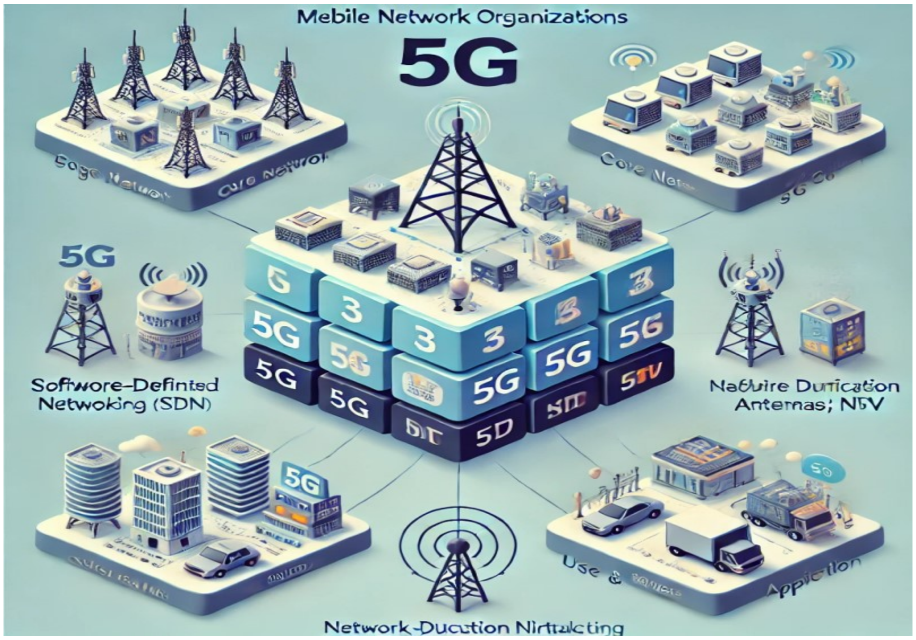

Figure 4: Mobile Network Organizations

	Time	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	12:00:00 AM	10	Tuesday	31	0	4	4	39	low
1	12:15:00 AM	10	Tuesday	49	0	3	3	55	low
2	12:30:00 AM	10	Tuesday	46	0	3	6	55	low
3	12:45:00 AM	10	Tuesday	51	0	2	5	58	low
4	1:00:00 AM	10	Tuesday	57	6	15	16	94	normal

Figure 5: Sample Dataset

3.6. Machine Learning Strategy

Numerous ML techniques were carried out to replicate the public dataset based on the Traffic Prediction Dataset. Comprising 18 features overall, this dataset represents data gathered online. Figure 5 shows the top 5 features that the simulation is attempting to accomplish using the Traffic Prediction dataset.

Several machine learning techniques, including XGBoost, CatBoost, Random Forest, and Logistic Regression, are used to allocate slices for a service in an efficient manner. Using a collection of data that has been divided into testing and training sets, we evaluate each approach.

3.6.1 XGBoost

The XGBoost model is widely used in 5G network traffic prediction due to its efficacy in processing large datasets and identifying complex patterns shown in Table 1. This kind of analysis often utilizes time-series traffic data collected from real or simulated 5G networks, including parameters such as UE ID, cell ID, signal strength, bandwidth usage, latency, packet loss, and historical traffic volume, among others. These datasets facilitate the enhancement of Quality of Service, optimization of resource allocation, and prediction of future network congestion. Standardization, feature selection, and handling of missing values are prevalent preprocessing strategies for enhancing model correctness and performance in dynamic 5G environments.

Table 1: Pseudocode for XGBoost Classification.

Algorithm 1: Pseudocode for XGBoost Classification
Step 1: Data Preprocessing - Load the 5G network traffic dataset. - Clean the dataset by handling missing values and normalizing features. - Create training and assessment sets from the

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material.
Step 2: Feature Engineering
- Extract relevant features such as signal strength, bandwidth usage, and latency.
- Create additional time-based features to capture traffic trends.
Step 3: Model Training
- Initialize XGBoost with appropriate hyperparameters.
- Put the training dataset through its paces.
Step 4: Prediction and Evaluation
- Apply the trained model to predict traffic on the test dataset.
- Run the numbers through an assessment tool to get measures like RMSE and MAE.
Step 5: Model Optimization and Deployment
- Tune hyperparameters and refine feature selection.
- Deploy the optimized model for instantaneous traffic prediction in 5G networks.

3.6.2 CatBoost

CatBoost is an effective machine learning model for forecasting traffic in 5G networks, especially with time series and categorical data shown in Table 2. Datasets often include timestamped network traffic information characterized by signal strength, bandwidth usage, latency, user equipment (UE) ID, cell ID, and historical traffic volume. CatBoost uses ordered boosting to mitigate overfitting and adeptly manages categorical variables with minimal preprocessing requirements. The dataset enhances network efficiency, optimizes resource distribution, and predicts traffic fluctuations. Preprocessing includes normalizing numerical features, rectifying absent values, and encoding classification variables. The model is suitable for real-time traffic forecasting because of its robustness in dynamic 5G environments.

Table 2: Pseudocode for CatBoost Classification.

Algorithm 2: Pseudocode for CatBoost Classification
Step 1: Data Preprocessing
- Load the 5G network traffic dataset.
- Identify categorical and numerical features.
- Manage numerical data with missing values and apply normalization.
- Properly encode categorical factors.
- Create training and test sets out from the dataset.
Step 2: Feature Engineering
- Extract important features such as signal strength, bandwidth usage, and latency.
- Create time-based features to capture traffic trends.
Step 3: Model Training
- Initialize CatBoost with appropriate hyperparameters.
- Train the model using the training dataset while leveraging categorical feature handling.
Step 4: Prediction and Evaluation
- Apply the trained model to classify traffic patterns on the test dataset.
- Determine the model's efficacy by calculating its F1 score, accuracy, precision, and recall.
Step 5: Model Optimization and Deployment
- Find the sweet spot for feature selection and hyperparameter tuning.
- Deploy the model for real-time 5G network traffic classification and monitoring.

3.6.3 Random Forest

Random Forest is a robust ensemble learning algorithm recognized for its durability and proficiency in dealing with data that has several dimensions of 5G network traffic predictions shown in Table 3. Timestamped network traffic logs often include elements such as user equipment (UE) ID, cell ID, signal strength, bandwidth usage, latency, packet loss, and historical traffic volume. Random Forest mitigates overfitting and adeptly manages missing data by constructing aggregate results of multiple decision trees to offer accurate predictions. The dataset facilitates enhancements in quality of service (QoS), optimization of resource allocation, and predictions of network congestion. In dynamic 5G environments, feature selection, normalization, and categorical data processing enhance model efficacy.

Table 3: Pseudocode for Random Forest Classification.

Algorithm 3: Pseudocode for Random Forest Classification
Step 1: Data Preprocessing
- Load the 5G network traffic dataset.
- Identify numerical and categorical features.
- Handle missing values and normalize numerical data.
- Separate the dataset into two halves, one for training and one for testing, then encode the categorical variables.
Step 2: Feature Engineering
- Extract key features such as signal strength, bandwidth usage, latency, and traffic volume.
- Generate additional time-based features to

capture temporal patterns. **Step 3:** Model Training - Initialize the Random Forest classifier with a defined number of trees. - Train the model using the training dataset while handling feature importance. **Step 4:** Prediction and Evaluation - Apply the trained model to classify traffic patterns on the test dataset. - Determine success by calculating the F1-score, recall, accuracy, and precision. **Step 5:** Model Optimization and Deployment - Fine-tune hyperparameters such as tree depth and the number of estimators. - Deploy the optimized model for real-time 5G network traffic classification.

3.6.4 Logistic Regression

Logistic regression is a widely used arithmetical model for forecasting 5G network traffic, particularly in tasks requiring binary or multi-class classification shown in Table 4. Timestamped traffic logs often include attributes such as user equipment (UE) ID, cell ID, signal strength, bandwidth utilization, latency, packet loss, and historical traffic patterns. Logistic regression employs a sigmoid function to model the association between input factors and traffic outcomes, therefore estimating the probability of network congestion or service deterioration. Addressing absent values, normalizing numerical data, and encoding category variables exemplify preprocessing techniques. The model is suitable for real-time traffic classification in dynamic 5G environments owing to its efficiency, interpretability, and simplicity.

Table 4: Pseudocode for Logistic Regression Classification.

Algorithm 4: Pseudocode for Logistic Regression Classification
Step 1: Data Preprocessing - Load the 5G network traffic dataset. - Identify numerical and categorical features. - Handle missing values and normalize numerical data. - Encode variables with categories and partition the dataset into training and testing subsets. **Step 2:** Feature Engineering - Select relevant features such as signal strength, bandwidth usage, latency, and traffic volume. - Create additional time-based features to capture traffic trends. **Step 3:** Model Training - Initialize the Logistic Regression model with appropriate settings. - Train the model using the training dataset to learn feature relationships. **Step 4:** Prediction and Evaluation - Apply the trained model to classify traffic patterns on the test dataset. - Assess model efficacy using accuracy, precision, recall, and F1-score. **Step 5:** Model Optimization and Deployment - Tune hyperparameters such as regularization strength. - Deploy the optimized model for real-time 5G network traffic classification and monitoring.

4. RESULTS AND DISCUSSION

Researchers created a method that facilitates ONSSA engagements in multi-domain slicing environments by the use of decision-making methodologies and machine learning to validate the proposed solution. This method focuses on assessing and dynamically mapping sufficient QoS standards by keeping an eye on MNO network traffic activities and creating a template for generating slices in various formats.

The dataset was used to demonstrate machine learning algorithms for slice allocation across different split ratios. We used the NVIDIA GPU for the precision and simulation of Anaconda Python. To test the suggested methodology, we conducted experiments to develop a system facilitating ONSSA operations in multi-domain slicing situations via machine learning and decision-making techniques. This methodology emphasizes evaluating and dynamically mapping appropriate QoS needs by analyzing network traffic from MNOs and creating a template for generating slices in many formats. Models on testing data generate accuracy; so, the split-ratio shows training and testing of the data. In this sense, all approaches to machine learning provide great accuracy shown in Table 5.

Random Forest, CatBoost, Logistic Regression The regression accuracy in this context surpasses that of the XGBoost method. The slice allocation strategy for this accuracy may enhance the capacity of 5G networks. In the long run, with deployment, these algorithms may provide classification accuracy above 98.85%.

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Table 5: Different Slices for Machine Learning Performance Accuracy Results.

Data Slice Ratio	XGBoost	CatBoost	Random Forest	Logistic Regression
80:20	93.10%	94.52%	98.10%	98.08%
70:30	93.18%	94.85%	98.12%	98.05%
90:10	93.59%	94.98%	98.54%	97.85%
85:15	94.10%	94.99%	98.85%	97.98%

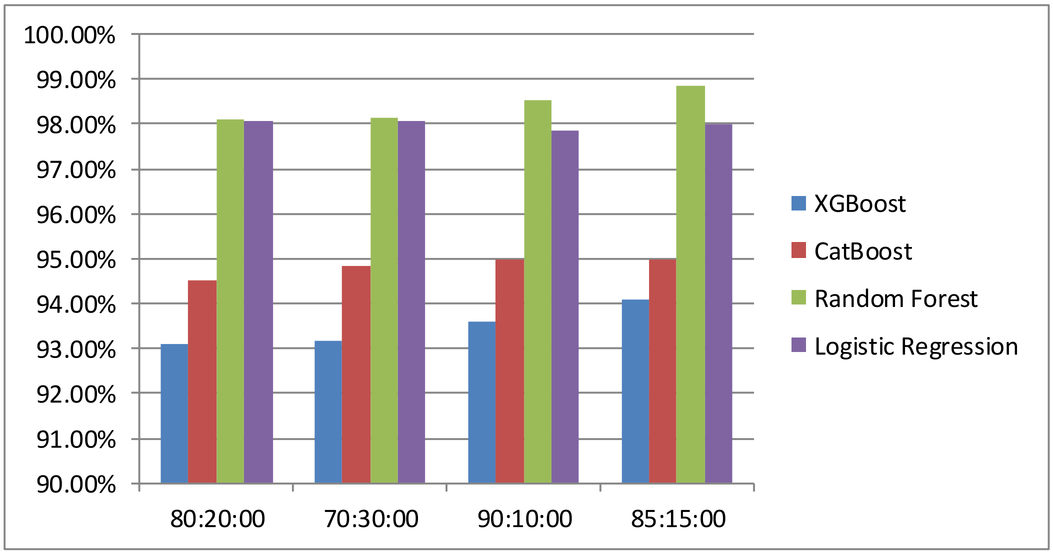

Figure 6: Machine Learning Performance Accuracy Results with Different Slices

4.1 Performance Measurements

Figure 6 compares the four machine learning models' classification accuracy—XGBoost, Catboost, Random Forest, and Logistic Regression—on a 5G network traffic prediction dataset using different data slice ratios for training and testing. The ratios considered are 80:20, 70:30, 90:10, and 85:15. CatBoost consistently outperforms XGBoost, with accuracy ranging from 94.52% to 94.99%, highlighting its efficiency in handling categorical data and boosting performance. Random Forest achieves the highest accuracy, ranging from 98.10% to 98.85%, demonstrating its robustness in classification tasks. XGBoost shows a stable accuracy between 93.10% and 94.10%, making it a reliable model but slightly less effective than CatBoost. Logistic Regression performs well but has slightly lower accuracy, between 97.85% and 98.08%, indicating its limitations in complex, non-linear data patterns. Overall, Random Forest proves to be the best performer, followed by CatBoost, while Logistic Regression remains a simpler but effective alternative.

This work offers the computational capacities required to concurrently train and assess many artificial intelligence models. The simulation environment accommodated LLC slices that ensure latency under 1 ms with bandwidth between 2 and 30 Mbps; MNO slices that support device concentrations of up to 10 million gadgets per square kilometer; and MNO slices that span 1000 Mbps to 200 Gbps. The use of lazy prediction, logistic regression (LR), and fine-tuning facilitates the simplification of the orchestration process. These technologies enable choosing a machine learning method depending on the surroundings, therefore enhancing the process. The LazyPredict module, equipped with performance metrics, automates the algorithm selection procedure. The Slice Orchestrator's Network Slice Capabilities Analyser and Network Sub-Slice Mapper modules utilize it to independently assess and choose the most appropriate supervised learning methods for their specific applications. This method evaluates around four methods for machine learning in the monitored surroundings, significantly reduces the time and effort needed for manual testing, and aids in the rapid identification of the best algorithms for the current resource allocation issues. Future algorithms may be included in the suggested design to make use of the LazyPredict Python package when new methodologies are discovered and introduced into the Python ecosystem. This guarantees that considering recent breakthroughs in machine learning approaches, our system will stay pertinent and flexible.

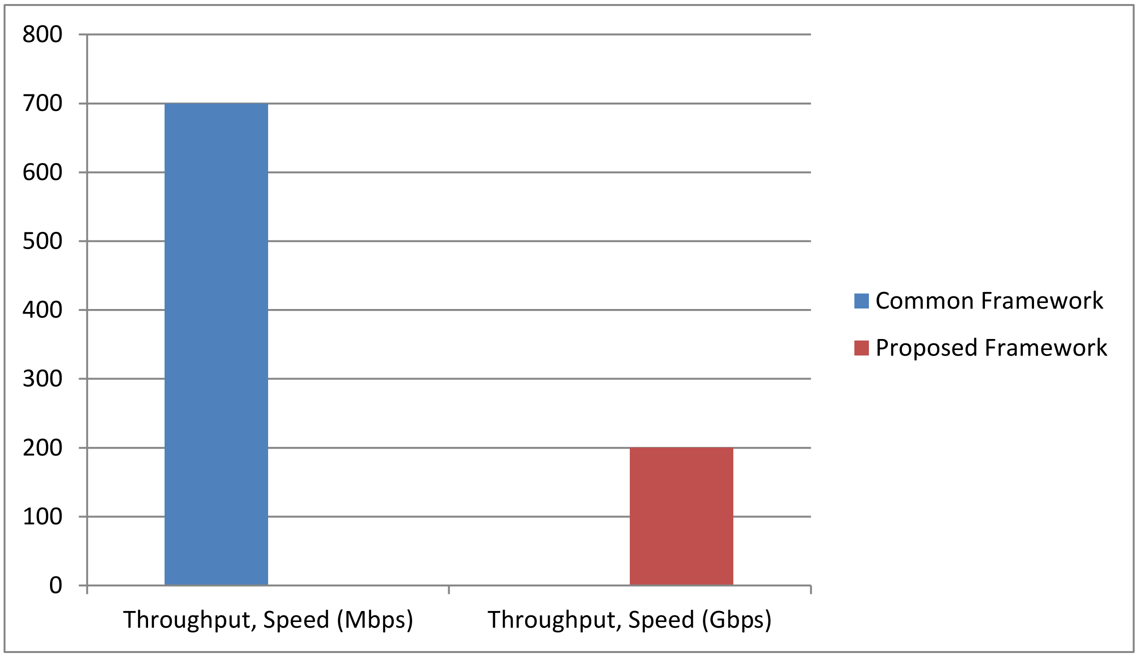

Figure 7: Throughput Result

Table 6: Throughput for Common and Proposed Framework.

Measurements	Common Framework	Proposed Framework
Throughput, Speed (Mbps)	700 Mbps	200 Gbps

Table 6 and Figure 7 compare throughput speed between a conventional framework and a suggested framework. The conventional framework attains a peak speed of 700 Mbps, whereas the suggested framework markedly surpasses it with a speed of 200 Gbps. This signifies a substantial enhancement in data transfer capabilities, making the suggested architecture more appropriate for high-speed applications such as 5G networks, cloud computing, and extensive data transmission. The picture graphically illustrates this disparity, emphasizing the significant increase in throughput. This development indicates that the suggested framework is capable of managing a much greater amount of network traffic, hence enhancing overall efficiency and performance.

Table 7: Latency for Common and Proposed Framework

Measurements	Common Framework	Proposed Framework
Latency, Time (ms)	90 ms	350 ms

Table 7 and Figure 8 contrast the latency performance of a conventional framework with that of a suggested framework. The typical framework demonstrates a delay of 90 milliseconds (ms), but the suggested framework reveals a much greater latency of 350 ms. This indicates that, although possible enhancements in other domains, the suggested framework incurs a delay in data transmission, thus detrimentally influencing real-time systems like cloud computing, video streaming, and online gaming. The image clearly illustrates this distinction, underscoring that while the suggested architecture may excel in throughput or other metrics, its heightened latency might represent a significant constraint in time-sensitive operations.

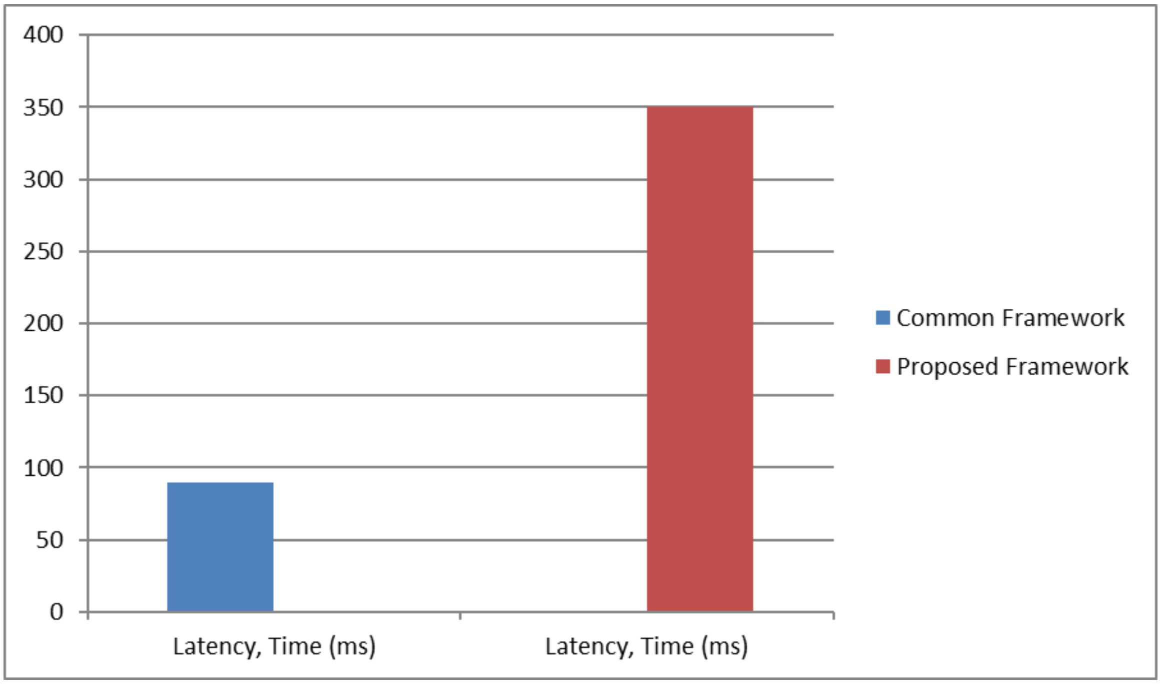

Figure 8: Latency Result

Table 8: Prior Research Comparison Table

References	Framework	Security Mechanism	Attack Prevention
[24]	Slicing, cryptography, and authentication are the means by which networks are isolated.	Isolation of Slices	No
[25]	Network slicing in 5G IoT architecture	IDS	No
[26]	An end-to-end 5G network security solution based on a hierarchical detection technique using reinforcement learning was suggested	AR, V2V	No
Proposed	The proposed architecture is to identify and mitigate known 5G Network Slicing vulnerabilities in real time. It created a service function chaining protocol layer and reduced control channel overhead using P4-based switches	ONSSA, MNO, DCNaaS	Yes

4.2 Prior Research

The existing and proposed 5G solutions, as well as 5G security services, network slicing, its uses, and related security concerns. There will be sea changes in mobile communication and technology brought forth by the improved 5G mobile network. It supports Augmented Reality (AR) and Internet of Things (IoT) communication protocols, as well as Vehicle-to-Vehicle (V2V) communication between vehicles and other devices. Features like scalability, availability, reliability, and mobility are available in the 5G network. Critical application security requirements such as availability, confidentiality, authentication, authorization, data integrity, and privacy are also met. Table 8 shows the prior research comparison table.

5. CONCLUSION

Particularly in allocating resources, network division, and network management of dynamic events, the development of 5G and later networks offers hitherto unheard-of possibilities and challenges. This paper presented the proposed ONSSA structure, MNO model, and a unique DCNaaS approach using machine learning methods like Fine Tune the all-security aspects, LazyPredict, and AutoRL, therefore enhancing network slice

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organization. The allocation of the slice is addressed and resolved using machine learning techniques to meet the QoS and SLA requirements. Our model demonstrates superior performance on the used dataset; nevertheless, its efficacy will be enhanced when applied in real-time under active traffic conditions. In future projects, we want to use our methods in real-time. Furthermore, to enhance scalability, this initiative might be expanded via a deep learning system. While our proposed method demonstrates promising results, limitations include potential scalability issues in ultra-dense networks and dependency on accurate traffic prediction models. Additionally, simulation-based evaluations may not fully capture real-world variability, posing threats to external validity. Future work should explore deployment in live 5G environments to validate robustness and adaptability.

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