Exploration of NWDAF Development Architecture for 6G AI-Native Networks

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Abstract: Artificial intelligence (AI)-native communication is considered one of the key technologies for the development of 6G mobile communication networks. This paper investigates the architecture for developing the network data analytics function (NWDAF) in 6G AI-native networks. The architecture integrates two key components: data collection and management, and model training and management. It achieves real-time data collection and management, establishing a complete workflow encompassing AI model training, deployment, and intelligent decision-making. The architecture workflow is evaluated through a vertical scaling use case by constructing an AI-native network testbed on Kubernetes. Within this proposed NWDAF, several machine learning (ML) models are trained to make vertical scaling decisions for user plane function (UPF) instances based on data collected from various network functions (NFs). These decisions are executed through the Kubernetes API, which dynamically allocates appropriate resources to UPF instances. The experimental results show that all implemented models demonstrate satisfactory predictive capabilities. Moreover, compared with the threshold-based method in Kubernetes, all models show a significant advantage in response time. This study not only introduces a novel AI-native NWDAF architecture but also demonstrates the potential of AI models to significantly improve network management and resource scaling in 6G networks.

Keywords: 6G; AI-native; NWDAF; UPF scaling

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1 Introduction

With the rapid advancement of mobile communication technologies, 6G communication networks have gained widespread attention as the next frontier in modern communication systems. A characteristic of 6G networks is the integration of artificial intelligence (AI) and network architecture, a concept termed AI-native communication[1]. The convergence of AI and communication technologies will transform network operations, enabling autonomous decision-making, dynamic resource management, and seamless adaptation to changing network conditions[2]. Meanwhile, AI-native communication has become a critical enabling technology for 6G, capturing the attention of academic and industrial communities worldwide. However, realizing AI-native communication functionality requires a robust foundation of supporting technologies to ensure flexibility, scalability, and efficiency for network operations. As an essential component of AI-native networks, the core network (CN) facilitates real-time data collection and intelligent resource scheduling[3]. By embedding AI directly into its architecture, the CN ensures seamless coordination among different network functions (NFs), enabling the dynamic adaptability and scalability essential for 6G networks[4]. Therefore, technologies such as network function virtualization (NFV), software-defined networking (SDN), and containerization have also been integrated into research on the intelligent evolution of the CN. NFV transforms dedicated NFs into virtualized software instances[5], reducing dependence on dedicated hardware and simplifying the AI-native network architecture. This also enables the seamless integration of AI models into network management, control, and optimization. SDN decouples the control and data planes, enabling centralized management and dynamic routing optimization, which supports real-time monitoring and adjustment of data flow paths, creating improved network conditions for AI models[6]. Additionally, containeriza-

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tion provides modularity and lightweight deployment capabilities, allowing efficient deployment, management, and updating of AI models, thus providing flexible, efficient, and scalable infrastructure support for AI-native networks[7]. Although these techniques improve the flexibility, robustness, and efficiency of the CN, enabling better deployment and resource flexibility for AI-native networks, they alone are insufficient to fully realize the potential of AI-native capabilities[8]. Bridging this gap requires the incorporation of advanced data analysis and decision-making mechanisms[9], which are essential for achieving the autonomous intelligence envisioned in AI-native networks. The network data analytics function (NWDAF) addresses this critical gap by serving as an independent intelligent NF introduced in the CN, as part of the 5G standard protocol proposed by the 3rd Generation Partnership Project (3GPP) first[10]. By leveraging the flexibility and scalability enabled by NFV, SDN, and containerization, the NWDAF integrates advanced data analytics and machine learning techniques to effectively process and analyze large-scale datasets within the CN.

NFV enables the NWDAF to be dynamically deployed and scaled on demand, allowing real-time adjustment of computing resources based on network traffic. SDN facilitates multidimensional data collection from various NFs while enabling flexible traffic management. Additionally, containerization enhances the adaptability of the NWDAF by supporting rapid deployment, migration, and scaling across diverse environments, thereby improving the modularity and scalability of the data analysis process. These enable the NWDAF to provide intelligent data-driven decision-making support for network optimization and management. Through sophisticated data processing and predictive modeling, the NWDAF addresses critical challenges in modern networks, including resource allocation, load balancing, and fault recovery[11]. As a result, it facilitates the evolution of the CN from traditional reactive management to more intelligent and autonomous operational models, paving the way for more efficient, adaptive, and dynamic network management[12].

Despite the significant flexibility and intelligent potential demonstrated by the NWDAF through the integration of NFV, SDN, and containerization technologies, its efficient implementation still faces two core challenges. First, data collection serves as the foundation for both NWDAF and AI-native network implementation. Unlike traditional NFs, the NWDAF requires a comprehensive and real-time collection of network state data to support accurate analytics and decision-making[13]. This is particularly critical in scenarios such as user plane function (UPF) scaling, where real-time data on UPF load and resource availability must be continuously gathered to enable dynamic and efficient resource allocation. Second, AI-native capabilities demand the seamless embedding of AI into the network architecture rather than the standalone application of machine learning (ML) models[14]. Given the diversity of network scenarios, the NWDAF must include a dedicated function to manage the training, storage, and dynamic orchestration of various AI models, ensuring adaptability and scalability in meeting specific operational requirements. Specifically, in the context of UPF optimization, the NWDAF can facilitate seamless UPF scaling to accommodate varying traffic demands thus optimizing network performance. In light of these challenges, existing research has investigated various aspects of these challenges. For instance, MEKRACHE et al. proposed a microservice architecture for the NWDAF, employing a Long Short-Term Memory (LSTM) auto-encoder to detect abnormal traffic generated by user equipment (UE), utilizing the Milano dataset for network data analysis[15]. Furthermore, NISHA et al. proposed a network load prediction and anomaly detection method and tested it using various machine learning methods[16]. Their work employed a comprehensive dataset supporting 5G networks. However, these studies primarily rely on publicly available or simulated datasets, focusing on optimizing network performance for a specific scenario, without implementing the complete pipeline from data collection to data analysis. SEVGICAN et al. proposed a system for intelligent network analytics using ML techniques, comparing the performance of multiple machine learning models[17]. MANIAS et al. proposed a prototype system for the NWDAF within the CN, employing data-driven techniques and unsupervised learning to analyze NF interactions[18]. ZHANG et al. applied fair federated learning (FL) to the 3GPP-standard NWDAF architecture, integrating a multi-task ML model for anomaly traffic detection across different types of user devices[19]. Most existing studies focus on singular optimization tasks, often overlooking the comprehensive management of the model lifecycle. As a result, critical aspects such as real-time data collection, dynamic model training, and model orchestration across various scenarios remain underexplored. This limitation significantly hinders the practicality and generalization capability of models in real-world network environments. To address these challenges, this paper makes the following contributions:

1) An AI-native NWDAF architecture is designed to integrate the functionalities for data collection and management, providing a solution for complex data processing in 6G network environments.

2) A specialized module for model training and management is designed to enable dynamic adaptation of AI models to diverse scenarios, effectively meeting the intelligent management requirements of 6G networks.

3) An AI-native network testbed is constructed to evaluate the designed architecture functionalities, including data collection, model training, and management. Meanwhile, the UPF scaling scenarios are adopted to validate the feasibility and effectiveness of the proposed architecture.

The rest of the paper is structured as follows: Section 2 introduces the AI-native NWDAF architecture. Section 3 discusses system deployment and experimental validation.

Section 4 concludes the paper and outlines directions for future research.

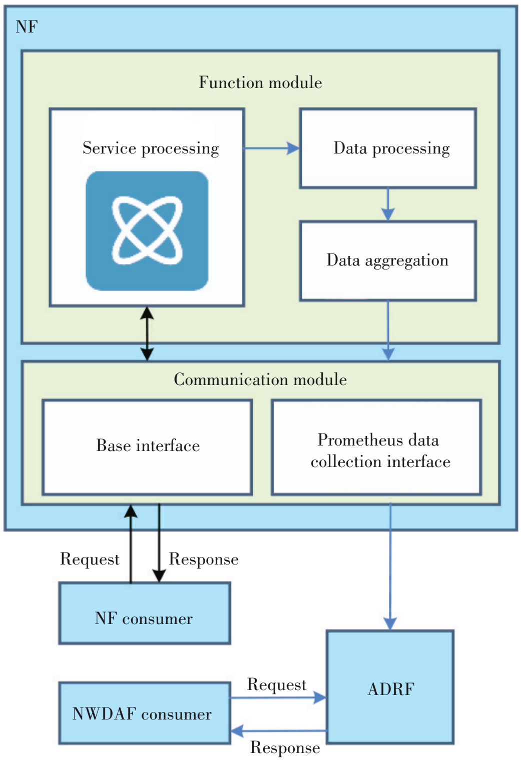
2 System Architecture

To enhance the intelligent capabilities of the 6G CN, this paper proposes a systematic approach through a novel NWDAF architecture. As shown in Fig. 1, the proposed system architecture comprises two layers: the infrastructure layer and the NWDAF service layer. The infrastructure layer is implemented on Kubernetes, providing functionalities for network monitoring and optimization. It detects the network environment, orchestrates network instances, and provides network data to NWDAF consumers for optimization through intelligent algorithms. The NWDAF service layer contains required NFs to implement the CN, with each NF independently deployed using the containerization technology. The NWDAF functional architecture consists of two key components: data collection and management (DCM) and model training and management (MTM). DCM is responsible for data collection, storage, and distribution, ensuring a continuous supply of high-quality data for the MTM. MTM focuses on model training and analysis, while managing various ML models to adapt to specific scenarios. The proposed architecture encompasses the entire process from data collection to model training and application, enabling the system to achieve autonomous decision-making. Compared to traditional network architectures or those with externally attached AI components, it provides enhanced flexibility and intelligence.

2.1 Data Collection and Management

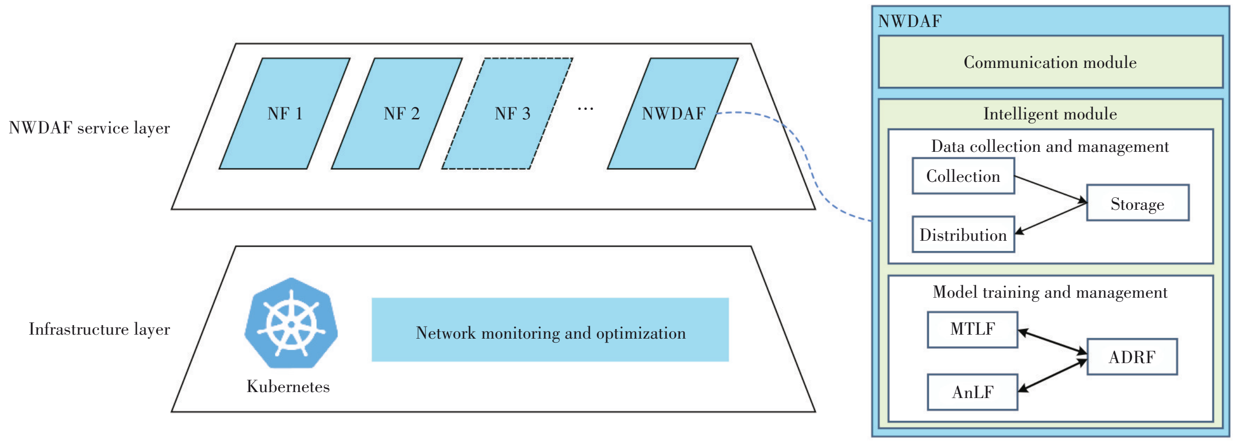
DCM serves as a fundamental component of the proposed architecture, functioning as the basis of model training and analysis. This module encompasses three functions: data collection, data storage, and data distribution. NWDAF collects data from multiple NFs, including the access and mobility management function (AMF), session management function (SMF), and UPF, which is subsequently stored for subsequent analysis and utilization.

To achieve efficient data collection and management, the system leverages Prometheus as the data collection framework. As illustrated in Fig. 2, each NF consists of two modules: the



ADRF: analytics data repository function
NF: network function
NWDAF: network data analytics function

Figure 2. Data collection and management



ADRF: analytics data repository function
AnLF: analytics logical function
MTLF: model training logical function
NF: network function
NWDAF: network data analytics function

Figure 1. System functional architecture

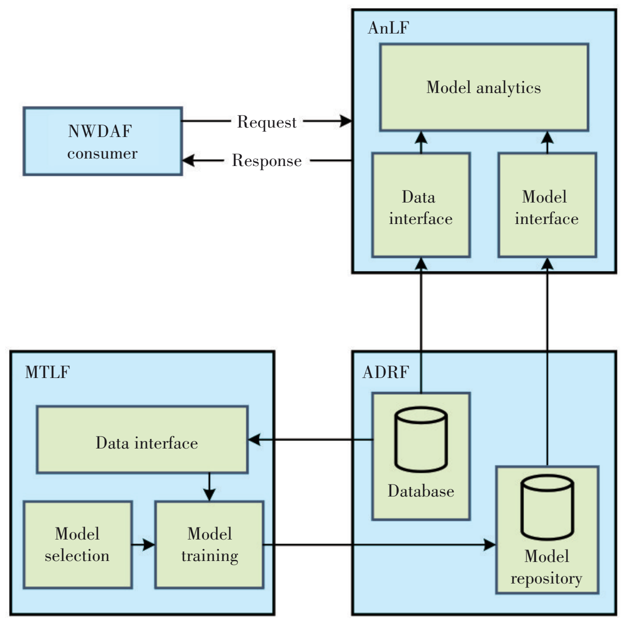
function module and the communication module. The function module implements all NF's functionalities and handles various services. The communication module manages external communication, comprising the system's base interface and the customized Prometheus data collection interface. The NWDAF performs data collection through the Prometheus data collection interface, which operates in parallel with the signal processing tasks within the NFs. This approach bypasses the base interface, such as traditional N-interface communication between NFs. This design not only avoids interference with the service workflows of the NFs, but also ensures high efficiency and reliability in the data collection process. Specifically, when an NF consumer initiates a processing request, the NF executes the task within its function module and returns the results to the consumer without interruption. Meanwhile, the specified data are recorded and stored in a cache. Subsequently, the data are processed and aggregated within the NF, and then uploaded to the analytics data repository function (ADRF) database via the data collection interface.

The ADRF database is implemented through Prometheus. It serves as a unified data storage center, which provides a reliable data source for subsequent model training and analysis. This architectural design enhances the flexibility of data management while laying a solid foundation for the NWDAF to realize AI-native capabilities.

2.2 Model Training and Management

MTM is a core component of the NWDAF and plays a pivotal role in realizing the intelligent capabilities of the CN. The MTM architecture, as shown in Fig. 3, encompasses three key components: the model training logical function (MTLF), analytics logical function (AnLF), and ADRF. MTLF serves as the central component for training ML models within the NWDAF. It acquires the required data from the ADRF database through the data interface, where the data is preprocessed to ensure data quality, format, and consistency. Subsequently, the selected model is trained using the prepared data. Once training is completed, the trained model weights can be saved and stored in the specific model repository of the ADRF. Additionally, historical data from the ADRF can be used for external model training, with the corresponding model weights saved in the same model repository of the ADRF. The AnLF is responsible for analyzing real-time data generated by the network, using models trained by the MTLF and generating relevant analysis results. By analyzing diverse network datasets, the AnLF supports applications such as traffic prediction, network load balancing, and anomaly detection, thereby facilitating intelligent network optimization. The AnLF incorporates both data interfaces and model interfaces. The data interfaces enable the AnLF to acquire necessary network data from the ADRF and other NFs, ensuring that analyses are based on the latest data. Meanwhile, the model interfaces allow the AnLF to dynamically select and apply the most appropriate trained models, ensuring optimal performance in different scenarios. Upon completion of the model analysis, the AnLF feeds the results back to the NWDAF consumer. These results can be directly utilized for decision-making to enhance overall network intelligence. Beyond model training and analysis, model storage emerges as a critical consideration in the NWDAF. In this system, the MTLF and AnLF specifically focus on model training and analysis, without incorporating model storage. Consequently, an independent machine learning model storage module is implemented. Following model training in the MTLF, information such as version numbers and training time is stored alongside the model repository. This system facilitates version management, access control, and state monitoring through the model management function.

The design of the MTLF offers significant advantages in improving the performance and resource utilization of 6G networks, promoting AI-native capabilities in 6G. Through the coordinated operation of its three modules, the system can address single optimization objectives such as load balancing, as well as multiple optimization objectives like improving energy efficiency. Due to the complexity of network environments, a single model often cannot perform well in all scenarios. Therefore, the MTLF trains multiple models based on different NFs and scenarios, which are stored in the ADRF database. Once the NWDAF receives a service request from an NF consumer, the system deploys the most optimal model for that NF. For example, in the case of UPF scaling, the system queries the model repository for models that can meet the UPF scaling re-



ADRF: analytics data repository function
AnLF: analytics logical function
MTLF: model training logical function
NWDAF: network data analytics function

Figure 3. Model training and management

quirements. Then, based on a predefined configuration table, the optimal model is selected by considering factors such as prediction time and model deployment time. This approach improves network performance and resource efficiency, offering a practical solution for realizing AI-native capabilities in 6G networks.

3 System Deployment and Experimental Validation

To evaluate the feasibility of the proposed system, a testbed is constructed based on Kubernetes. Each NF is encapsulated in a dedicated container and managed through unified orchestration and deployment using Kubernetes. Subsequently, a UPF scaling experiment is conducted on the testbed to validate the intelligent capabilities of the system.

3.1 Deployment Strategy

The testbed leverages the open-source CN framework Open5GS as its foundation, which provides essential functions including the AMF, SMF, UPF, etc. Since Open Source 5G System (Open5GS) does not natively support the NWDAF, we develop and integrate a custom NWDAF, equipping it with capabilities for data collection and model training. To support wireless signal processing, this testbed integrates OpenAirInterface5G (OAI) and deploys Universal Software Radio Peripheral (USRP) B210 to implement a Next-Generation Node B (gNB) and UE, effectively simulating real-world 5G network scenarios. The testbed adopts a microservice architecture utilizing containerization, encapsulating each NF as an individual container. Containers with similar NFs are strategically deployed on the same node, facilitating rapid updates, deployments, and scaling of NFs while ensuring fault isolation and improving system resilience. As illustrated in Fig. 4, the system's deployment structure comprises two servers designated as Control Plane and User Plane nodes within the CN. The Control Plane node hosts the AMF and SMF, while the User Plane node houses the UPF. Additionally, the gNB is encapsulated as a container and deployed on a dedicated Kubernetes node. To enable real communication, USRP B210 is connected to the host running the gNB container. Similarly, UE is deployed directly on its host and connected to another USRP B210 device to facilitate connectivity to the gNB.

3.2 Experiments

The experiments aim to validate the auto-scaling capabilities of the UPF and are conducted on the previously described testbed. The setup involves connecting four PCs to USRP B210 devices, utilizing OAI to simulate two user devices and two gNBs, which establish connectivity to the CN. This configuration enables two user devices to access the CN, with load generation on the UPF being achieved through data packet transmission between the user devices using the iPerf tool. The experiment simulates and verifies the process of vertical scaling. As shown in Fig. 5, vertical scaling involves increasing the resource allocation of a single pod, including CPU cores, memory capacity, and storage, to handle increased load. During the experiment, real-time data are collected and analyzed to ensure the system operates normally. Several key metrics from the AMF, SMF, and UPF are tracked to monitor the experiment process, including UPF metics such as traffic, CPU usage, and Radio Access Network (RAN) data (e.g., UE uplink/downlink traffic and bitrates). A total of 26 metrics related to UPF scaling are collected, including UPF CPU usage, the data transfer rate, and the uplink/downlink throughput of UE. These data, comprising 600 samples, are continuously collected over a 10-minute period and utilized in model training. The UPF CPU usage after 30 s is used as the prediction target, while other collected related data serve as the training param-

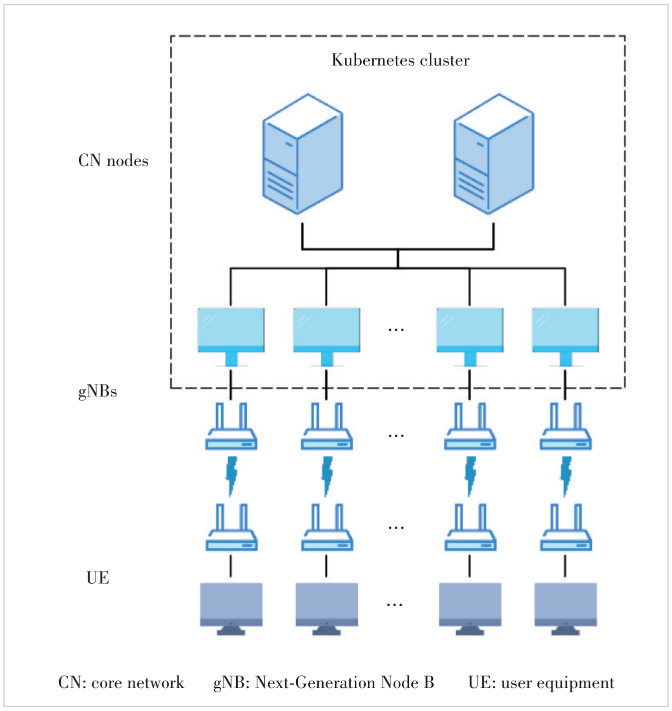


Figure 4. System deployment structure

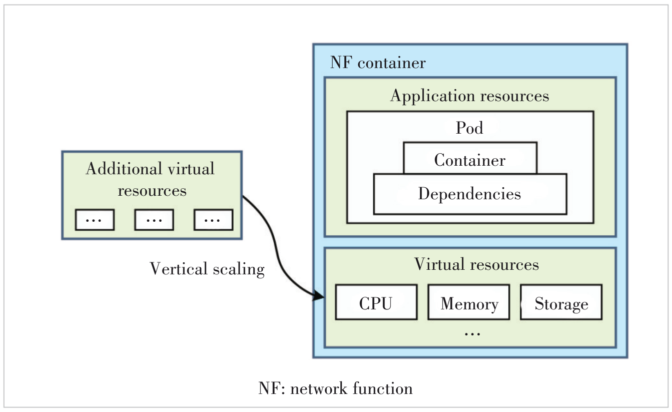


Figure 5. Vertical scaling of NF container

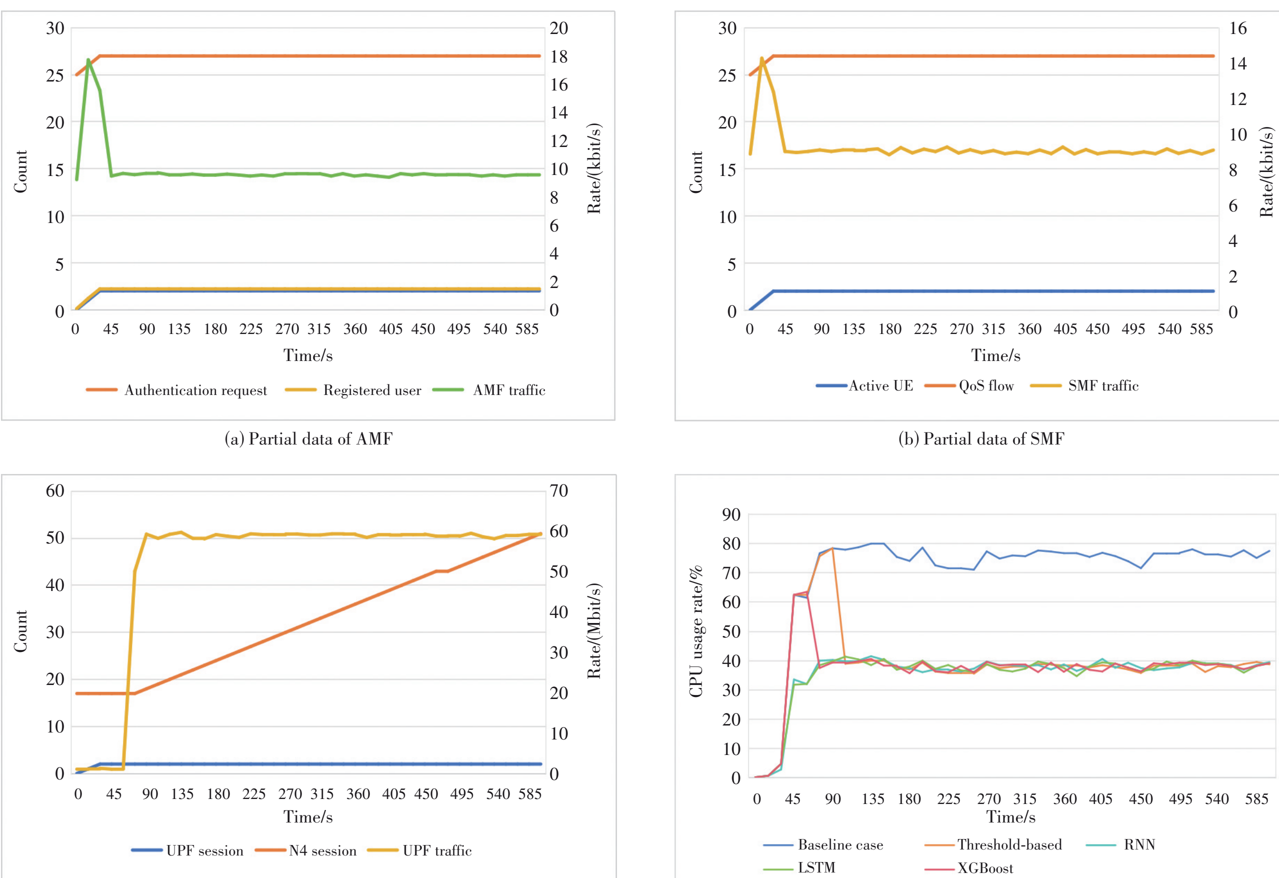
eters. When the predicted UPF CPU usage after 30 s exceeds 70%, a UPF vertical scaling operation is triggered.

To evaluate the performance of UPF scaling across various scenarios, multiple ML models are trained using the collected data. These models include LSTM[20], Extreme Gradient Boosting (XGBoost)[21], and Recurrent Neural Networks (RNNs)[22]. The trained model weights are saved as files, offering advantages in terms of shareability and reduced storage requirements. They are subsequently stored in a dedicated model repository. Finally, these models are invoked in the simulated environment, and scaling strategies are implemented based on the prediction results through the Kubernetes API.

3.3 Results

At the outset of the experiment, the relevant data from the AMF, SMF, and UPF are collected. As shown in Figs. 6a, 6b, and 6c, the data, including the number of user devices successfully connected and the number of UPF sessions, indicate that both user devices are successfully connected to the CN. Throughout the UE connection process to the CN, a large number of requests are generated, leading to an increase in network traffic of the AMF and SMF around the 15th second, followed by a quick decline. N4 sessions refer to session instances created between the SMF and UPF to ensure communication between the user plane and the control plane. Due to continuous data transmission, the number of N4 sessions increases to 50. Additionally, the UPF traffic values consistently remain around 60 Mbit/s during the communication process between the user devices, demonstrating successful data transmission between the terminals. These results indicate that when multiple user devices connect to the CN and engage in data transmission, the system successfully executes real-time data collection and analyzes the current system states.

Fig. 6d demonstrates how intensive data transmission between user devices leads to UPF scaling . The blue line represents the baseline case without scaling, while the other four lines show the results of using a threshold-based method and three ML models (LSTM, XGBoost, and RNN) for UPF scal-



(a) Partial data of AMF

(b) Partial data of SMF

(c) Partial data of UPF

(d) Comparison of UPF scaling effects

AMF: access and mobility management function
LSTM: Long Short-Term Memory
QoS: quality of service
RNN: Recurrent Neural Network
SMF: session management function
UE: user equipment
UPF: user plane function
XGBoost: Extreme Gradient Boosting

Figure 6. Data collection and algorithm comparison during the scaling process

ing. The results show that all three ML models successfully predict the increase in CPU utilization and trigger scaling. The threshold-based method also triggers scaling successfully. However, compared to the threshold-based method, all three ML models require significantly less time. In addition, Table 1 demonstrates the prediction accuracy of the three ML models. The results show that all three models achieve high accuracy, further confirming their satisfactory predictive capabilities. This experiment successfully validates the process of data collection and model analysis, demonstrating the advantages of using machine learning models for UPF scaling within the proposed architecture. Consequently, it further confirms the feasibility of the architecture presented in this paper.

Table 1. Prediction accuracy of the three models

Model	Accuracy/%
RNN	94.74
LSTM	94.87
XGBoost	86.84

LSTM: Long Short-Term Memory
RNN: Recurrent Neural Network
XGBoost: Extreme Gradient Boosting

4 Conclusions

This paper presents a novel NWDAF architecture designed to enhance the performance and scalability of AI-native 6G networks. The proposed architecture integrates data collection, model training, and analysis, providing a robust solution for dynamic network management. In addition, a testbed is established to conduct data collection and model training, validating the proposed framework with a specific focus on UPF overload and scaling scenarios. The experimental results demonstrate that the implementation of the ML models can effectively reduce the delay in UPF scaling, enhancing system responsiveness and performance. Future research directions include advancing the management of the ML models and exploring the comparative advantages of different models across various scenarios. Additionally, the integration of AI-native networks with multiple domains, such as edge computing, will be investigated to enhance real-time decision-making and resource allocation. Through these multi-domain integrations, the scalability, interoperability, and autonomous management of the network can be further enhanced.

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