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Efficient resource allocation through CNN-game theory based network slicing recognition for next-generation networks

Francikus Antonius [1,2]

Lecturer at School of Business and Information Technology STMIK LIKMI, Bandung, Indonesia

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ABSTRACT

Fifth generation (5G) and sixth generation (6G) networks are examples of next-generation networks that need higher levels of safety, lower latency, and more capacity and dependability. Reconfigurable wireless connection slicing becomes essential for satisfying these sophisticated networks' requirements, enabling many network instances on the same hardware to improve Quality of Service (QoS). Nonetheless, the centrally managed resource allocation for network slicers presents difficulties, particularly as the quantity of User Equipment (UEs) increases. This puts pressure on Radio Resource Management (RRM) and makes slice customization more difficult. In order to address these issues, this study presents an organizational radio resource distribution architecture in which the neighborhood radio resource managers (LRRMs) receive sub channel allocations from the RRM in slices, and the LRRMs then distribute the assigned capabilities to the corresponding UEs. The suggested model, which runs in MATLAB, uses an original method called CNN-Game Theory to achieve an exceptional 98 % accuracy, outperforming CNN-LSTM, RNN, DeepCog, and DHOA by 29.27 %. This method combines ideas from game theory with neural network weight optimization to produce an improved model with increased efficiency and accuracy. Many experiments illustrate how effective this method is and how it can be used to improve different machine learning applications. Metrics like slice type utilization, average packet delay for each LTE/5G category, and others are used to assess game optimization for resource allocation

Introduction

Given the growing number of mobile terminals (MTs), the fifth-generation (5G) wireless messaging network is expected to boost bandwidth through one million over the fourth-generation (4G) network while improve spectrum efficiency (SE) by 5 - 15 times [1–3]. In the past few years, an abundance of academics have advocated for the creation of Bluetooth cell phones, most with a focus on increasing wirelessly networks' capacity to deliver services related to communication [4–6] Mobile telecommunications has been aggressively chasing faster productivity, decreased latency, improved dependability, and greater reach for the past few years. Improving the distribution of restricted communication assets is additional successful strategy, in along with devising improved code, modification, channels calculation, equalizing, and detection/decoding algorithms [7]. The efficient use for electronic network capacities such distributing power aimed at spectrum and energy-efficient subcarrier task in orthogonal frequency-division multiple access (OFDMA) and multi-carrier non-orthogonal multiple access (NOMA), time allocation in time-division multiple access (TDMA), computation offloading in multi-access edge computing (MEC), remote radio head selection in cloud radio access network (C-RAN), and cluster-head choosing in cloud radio access network (C-RAN), and cluster-head choosing in cloud radio access network (C-RAN) choosing in portable [8,9]. Wireless networks are vital components of massive intelligent devices such as robots and the Internet of Things (IoT). The ideal equilibrium of the numerous benefits and limitations which determine the operational point of an enormous number of wirelessly linked devices is required for the development of such systems [10].

Over the past decade, the explosive development of cellular amenities, as well as improvements in the internet of things (IoT) other smart devices, has brought substantial problems in the 5G space. The volume of data is increasing as a result of new mobile apps like as augmented reality (AR), recognition of faces, and three-dimensional video broadcast [11,12]. By completely utilizing the knowledge production, reserve management, and storage capacity of edge machinery, proposed for attaining high spatial efficiency, cost effectiveness, and low latencies

E-mail address: franciskus.antonius.alijoyo63@gmail.com.

[1] https://orcid.org/0000-0002-5624-873X

[2] Founder and Principal of Center for Risk Management and Sustainability Studies Indonesia.

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[13,14]. Sophisticated commercial manufacture, including electricity networks, autos, and health-care, powered by Cyber-Physical Internet of Things Systems (CPIoTS), has emerged becoming an emerging worldwide tendency. CPIoTS, which enable coordinated including close connection among individuals and physical operations through relationships, may be viewed as a rapid progression of IoT [15]. The introduction of 5G has sparked interest as a response to the growing need for mobile information transmission. 5G has enhanced certain aspects that hadn't been well handled in the 4G network, which includes as greater data speeds, reduced end-to-end (E2E) delay, more dependability, and huge device interconnections [16]. Connecting tangible assets and facilities including self-driving automobiles and small power grids, to the Online is a crucial aspect of cyber-physical platforms for effective management, administration, and surveillance [17].

This innovative research study, efficient resource allocation through CNN-game theory based network slicing recognition for next-generation networks, addresses resource allocation optimization in the context of developing next-generation networks, specifically 5G and beyond [18]. Efficient resource allocation becomes critical as the global communication infrastructure transforms to satisfy the ever-increasing demands for diversified, high-speed, low-latency services. One of these advanced networks' primary architectural features, network slicing, enables the construction of autonomous, virtualized sub networks that are customized to meet particular application needs. It is a difficult task to allocate resources inside these slices in the best possible way [19].

This work addresses the complexities of network slicing detection and resource allocation by utilizing two potent paradigms: game theory and CNN. CNNs are used to interpret and comprehend the dynamic network circumstances and use patterns because of their proficiency in pattern recognition and feature extraction. In contrast, a more effective and fair distribution of resources is made possible by game theory, which provides a formal framework for modelling and optimizing the strategic interactions between network slices [20].

Developing a resource allocation system that can adjust to the dynamic and unexpected characteristics of next-generation networks is the ultimate aim of this study. The goal of the research is to improve these networks' quality of service, dependability, and performance by utilizing game theory and machine learning approaches. In addition to addressing the technical difficulties of network slicing, this study has the potential to revolutionize how we perceive and take use of the promise of future networks, especially in the areas of smart cities, Industry 4.0, healthcare, and the IoT. This study makes a vital and forward-thinking contribution to the field of telecommunications and network engineering by helping to build networks that can efficiently support a broad range of applications as the digital world changes.

Presently the need for matrix communication solutions is skyrocketing, both are the sorts of amenities available, and intelligent grids have emerged as the primary developmental trend and, eventually, the strategic aim of the electrical power industry. Network cutting employs technology centered around Software Defined Network (SDN) and Network Functions Virtualization (NFV) in response to various application situations and 5G needs [21,22] Key contribution.

- An organizational radio resource distribution architecture for reconfigurable wireless connection slicing in next-generation networks (5G and 6G).
- The architecture involves the introduction of neighborhood radio resource managers (LRRMs) responsible for distributing subchannels within slices, thereby alleviating the strain on the centrally controlled resource management.
- This approach enables efficient slice customization and improves the quality of service (QoS) for a large number of user equipments (UEs).
- Additionally, the article introduces a unique technique, CNN-Game theory based network, for maximizing weights within neural networks, resulting in enhanced accuracy and efficiency for various machine learning applications.

The structure of this article is organized as follows: Section 2 reviews previous research on problems using various optimization methodologies. Section 3 discussed about problem statement. Section 4 describe proposed method. Section 5 discusses the results and discussion. Section 6 concludes the paper.

Related works

Soud et al. [23] proposed achieve enhanced Quality of Service (QoS) through efficient networking slicing, an extremely efficient and quick information categorization system is necessary. Software Defined Networking (SDN) combined centralized networks resource control can provide extremely fine bandwidth management. But important investigations have centered on deep learning structures, that demand significant computing and storage needs of SDN controllers, resulting in restrictions of traffic categorization mechanisms in terms of speed and precision. To address this need, this article recommends known as Intelligent systems SDN Multi Spike Neural System (IMSNS) by employing a moderately Multi-Spike Return Neural Networks (MMSRNN) the controllers with time-dependent computer programming, resulting in substantial energy usage a decrease and true traffic recognition for determining which is the most proper network of things slice. Furthermore, additional intelligent Recurrent Neural Network (RNN) controllers with distributing load and slice breakdown scenario is proposed throughout this research. The recently published scientists used the following metrics: reliability, precision, recall, and F1-Score. Their simulations demonstrated that the proposed approach could give 5 % higher-quality network slices from 5G than a convolutional neural network (CNN).

Abbas et al. [24] proposed created an intent-based network slicer architecture capable of effectively slicing and managing the primary network and radio access network (RAN) services. That result is an entirely computerized technology in which customers only submit more advanced knowledge in the format of a set of intents/contracts over an internet slice, as well as the technology automatically distributes and establishes the resources that are required. Furthermore, for networks resource administration, a deep learning model called Generative Adversarial Neural Network (GAN) was deployed. Multiple evaluations were conducted run using the equipment to create three slices, whose indicate increased efficiency in terms of both latency and connectivity.

Messaoud et al. [15] proposed by the bid to increase IIoT computationally power while also addressing QoS happiness and personal information expressing difficulties, became one reinforcement learning (RL) has emerged as an intriguing strategy that the allocates collecting data and computation obligations across a network of things network of representatives, leveraging local processing ratings and the representative learning by yourself encounters. This study offers a unique deep RL method for federation and flexible network oversight and distribution of resources that will enable internet of things to deliver distinct QoS capabilities. The suggested Deep Federated Q-Learning (DFQL) methodology achieves this objective in two major steps: Initially we discuss an adaptive slices TP and SF modification approach that utilizes Multi-Agent deep Q-learning (MAQL) which aims to maximize self QoS needs in terms of performance and latency. Secondly, Deep Federated Learning (DFL) is presented to teach the Multi-Agent Self model and enable them to identify the optimum activity selection for both TP as well as SF that fulfill IIoT virtual networking slice QoS incentive by using pooled knowledge across individuals. The findings from simulations indicate the proposed DFQL framework outperforms previous techniques in terms of productivity.

Kim et al. [11] proposed the use of 5G network slicing, allowing an actual infrastructure to be divided into several logical relationships, maintains the distribution of network resources equilibrium among varying service categories and immediately demand for resources. Likewise, to the variable nature of sliced demands, including unknown actual time consumption of resources and varied needs, ensuring

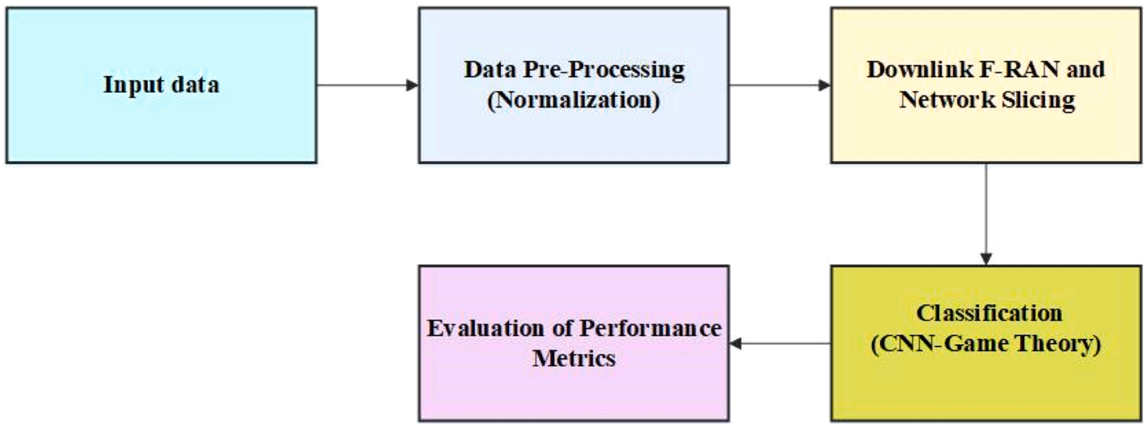

Fig. 1. Flow Diagram of Resource Allocation.

effective allocation of resources throughout the end-to-end system is challenging. The research presents an adaptive allocation of resources approach built around reinforcement learning (RL) for from end-to-end slices of networks with diverse needs in multi-layer MEC contexts. They initially create an organizational MEC framework and then use the Markov decision process (MDP) to solve a problem with optimization with distributing resources for throughout its entirety network splitting. Researchers use proximal policy optimization (PPO) to create both autonomous and cooperative dynamic capacity of resources techniques that optimize the utilization of resources while meeting slice QoS. Experimentation findings demonstrate that the suggested approaches can understand the features of slicing orders and upcoming resource needs and distribute services effectively while maintaining an exceptional QoS fulfilment rate.

Yan et al. [25] proposed resource scheduling is critical for optimizing resources-multiplexing efficiency between sliced and satisfying specified performance needs for RAN slicing. However, planning resources in RAN slices is extremely difficult owing to operational isolation, diverse service needs, and network structure (which incorporates user movement and carrier statuses, among other things). They present a sophisticated resource scheduling technique (iRSS) for 5G RAN sliced in this study. The fundamental idea of iRSS is to use a team-based instructional environment that combines deep learning (DL) with reinforcement learning (RL). In particular, DL is employed for large-scale allocating resources, whereas RL is utilized for via the internet resource planning in order to deal with small-scale dynamics of networks such as erroneous forecasting and unanticipated networking configurations. A variety of factors, including the quantity of readily accessible previous traffic data, iRSS may modify the importance of the predictions as well as online selection modules to aid the RAN with their resource allocation choices. When comparing to other benchmarking methods, the numerical findings suggest that the convergence stage of iRSS meets the criteria for electronically resource organization and may greatly enhance resource efficiency while ensuring economic isolation across slices.

This article investigates the establishment of a safe decentralized spectrum trade system for autonomously RAN slicing through the combination of blockchain-based technologies with NS [26]. In order to enable spectrum exchange for slice formation and autonomously slice adjustments among InPs and MVNOs, a consortium's blockchain platform is implemented in the suggested hierarchical architecture. In order to ensure efficient RAN slicing, the practice of spectrum trading incorporates underloaded MVNOs trading excess spectrum with overloaded MVNOs. A three-stage Stackelberg game paradigm is established combining InPs, seller MVNOs, and buyers MVNOs for optimum pricing and supply prediction techniques in order to solve incentive maximization. Then, to obtain a SE, a multi-agent deep reinforcement learning technique is utilized. The study culminates in a security evaluation and comprehensive simulation outcomes that validate the effectiveness of the suggested technique in optimizing players' utility and maintaining equity in contrast to other baseline methodologies.

This research presents a novel hierarchical structure for resource trade on blockchain inside the structure of RAN slicing, a key paradigm for 5G as well as beyond [27]. The suggested approach, which focuses on MVNOs' safe resource management difficulty, uses a consortium's blockchain system with hyperledger smart contracts to enable peer-to-peer resource trading. The importance of blockchain technology in addressing privacy and security issues that frequently impede cooperative resource trade in wireless communications is emphasized in the article. The price and demand problem is presented as a two-stage Stackelberg game, wherein seller MVNOs serve as leaders and buyer MVNOs play as consumers, in order to establish a fair reward mechanism. The suggested Dueling DQN approach improves autonomous resource allocation throughout negotiation intervals by achieving a SE for ideal pricing and demand policies. The efficiency of the suggested method is demonstrated by extensive simulation findings, which also show that it outperforms competing algorithms in terms of resource utilization, slice and system-level satisfaction, and a decrease in double spending assaults.

In order to solve the issues raised by next-generation networks like 5G and 6G, the literature study investigates a number of networking slicing techniques. In the first research, the Intelligent Systems SDN IMSNS is shown. It uses time-dependent programming and MMSRNN to improve traffic detection while consuming less energy. In order to optimize latency and connection, Abbas et al. suggest an intent-based network slicing design that makes use of GAN for network resource management. Messaoud et al. use DFQL to increase IIoT computational capacity and show increased productivity in simulations. Kim et al. demonstrate efficient resource use using an adaptive resource allocation strategy based on reinforcement learning for end-to-end network slices in MEC scenarios. In order to maximize resource multiplexing efficiency, Yan et al. propose a resource iRSS for 5G RAN slices that combines reinforcement learning and deep learning. The latter two studies address resource management issues faced by MVNOs by integrating blockchain technology with network slicing. In order to achieve optimal pricing and demand policies, both studies highlight the importance of blockchain technology and suggest hierarchical frameworks that utilize Dueling DQN and hyperledger smart contracts. These frameworks demonstrate superior performance in terms of resource satisfaction, security, and utilization.

Problem statement

The problem statement of this research article is to achieve enhanced Quality of Service (QoS) through efficient networking slicing. The

Table 1
Notations and Simulations Parameter.

Pj	jth distribution path between the starting vehicle and target vehicle
S	Collection of developed routing pathway in this scenario
Ts	Starting point for package delivery
Te	Packet forward ending time
$\boldsymbol{R_j(t)}$	Plan of player j at period t
P	Overall number of competitors
R	Methods used for selecting the relay vehicle
Uj	Usefulness of player j
$\boldsymbol{d_{ns1,q}}$	Point of $UE_{ns1,q}, c_{ns1,q,k,x}$
$\boldsymbol{b_{ns1,r,x}}$	Noise that corresponds to the distribution of $WM(0,\sigma^2)$
$\boldsymbol{UEn_{s1,q}\sum_k w_{ns1,q,k,x>0}}$,	RRH k the preceding vector intended for $UEns1,q$
L(x)	Outlier Rejection
σ	Standard Deviation
μ	Mean
$\widehat{d}$	Data normalization
$\log(d)$	Logarithmic normalization
R_p	Flexible Route Path
M	Minimal value

researchers aim to address the limitations of traffic categorization mechanisms in terms of speed and precision caused by the significant computing and storage needs of deep learning structures used in Software Defined Networking (SDN) controllers. They propose a solution called intelligent systems SDN Multi Spike Neural System (IMSNS) that employs moderately Multi-Spike Return Neural Networks (MMSRNN) in the controllers with time-dependent computer programming to reduce energy usage while achieving accurate traffic recognition. Additionally, they propose intelligent Recurrent Neural Network (RNN) controllers with load distribution and slice breakdown scenario [23].

Proposed method of network slicing recognition for resource allocation

Describe the architecture that involves RRM and LRRMs for efficient resource allocation. Explain how subchannels are distributed among LRRMs, and how LRRMs allocate resources to UEs. Discuss the advantages of this decentralized approach in handling growing numbers of UEs. Introduce the concept of CNN-Game theory based network for weight optimization. Explain the integration of game theory ideas in the weight optimization process. Compare this approach with conventional weight optimization techniques. Fig. 1. shows the Flow diagram of Resource allocation.

Data collection

The study efficient resource allocation through CNN-Game theory-based network slicing recognition for next-generation networks employed a network slicing recognition dataset that was sourced from Kaggle, a well-known platform for sharing and accessing datasets. The suggested CNN and game theory-based network slicing recognition model are likely to be trained and evaluated using this dataset, which presumably contains a variety of network-related data and parameters. Through the use of this dataset, the research sought to overcome the difficulties posed by dynamic network circumstances and the requirements of contemporary communication technologies by creating resource allocation algorithms in next-generation networks that are more effective [28].

LTE/5g - User Equipment categories or classes to define the performance specifications. Packet Loss Rate - number of packets not established divided by the total number of packets sent. Packet Delay - The time for a packet to be received. Slice type - network configuration that allows multiple networks (virtualized and independent). GBR - Guaranteed Bit Rate. Healthcare - Usage in Healthcare (1 or 0). Industry 4.0 - Usage in Digital Enterprises (1 or 0). IoT Devices – Usage. Safety for the Public - Use for community safety and well-being (1 or 0). Smart City & Home - application in regular domestic duties. Smart Transportation - its use in municipal systems. Smartphone - whether used for smartphone cellular data. These data modalities may be classified as a combination of network-related and application-specific data modalities, as well as categorical and binary data modalities. Table 1 indicates the notations and simulations parameters of the proposed algorithm.

Data pre-processing

Outlier rejection

From other views is a significantly deviated observation by the outlier. Classifiers are sensitive ranges and attribute distributions to data, so it must be excluded from data distribution. As shown in (1), the mathematical formulation in this paper for outlier rejection can be written as follows:

$$L(x) = \begin{cases} x, I_1 - 1.5 \times IQR \le x \le +1.5 \times IQR \\ \quad reject, otherwise \end{cases} \tag{1}$$

Fill in the missing or zero values

The process to fill in the missing or null values is after rejecting outlier attributes values as they can lead to incorrect prediction for any classifier. In the proposed architecture, mean attribute values, rather than omissions, are imputed with missing or null values that are expanded as in (2). The continuous data is imputed without introducing outliers, with the mean benefiting from imputation.

$$I(x) = \begin{cases} mean(x), ifx = null/missed \\ \quad x, otherwise \end{cases} \tag{2}$$

This feature vector $x$consists of instances in $n$space of dimensional, $x \in J^n$.

Normalization

Throughout the phase of preprocessing, aberrations are eliminated, missing data is added, and normalization is conducted. When a dataset is used to train a model, each feature's maximum follows a different distribution. In these situations, artificial neural networks have a difficult time matching the data. It tries to adjust each feature so that the real numbers set is similar in range. There are so many different techniques to solve this problem. For training and testing accepts some numerical values. In the dataset, numerical property values are encoded using on-hot encoding for all the symbolic to transmit property values. For example, dataset contains diabetes.csv. A numeric value is assigned to each symbolic attribute after the data has been transferred. To normalize the range of data properties, data scaling (data normalization) is used. Scale feature values using maximum-minimum normalization. A specific range of [1,2] due to (3) is normalized within all feature values.

$$\widehat{d} = \frac{d - d_{\min}}{dmin_{\max}} \tag{3}$$

Here denotes the sample value, indicates the minimal value and denotes each feature's maximum value.

(4) Provides information about the standard normal distribution that can be used to calculate a mean and a standard deviation for the data.

$$\widehat{d} = \frac{d - \mu}{\sigma}\widehat{d} = \frac{d - \mu}{\sigma} \tag{4}$$

Here is mean of (5):

$$\mu = \frac{1}{M}\sum\nolimits_{i=1}^{M} d_q \tag{5}$$

There standard deviation of is (6):

$$\sigma = \sqrt{\frac{1}{M}\sum\nolimits_{i=1}^{M}(d_i - \mu)^2} \tag{6}$$

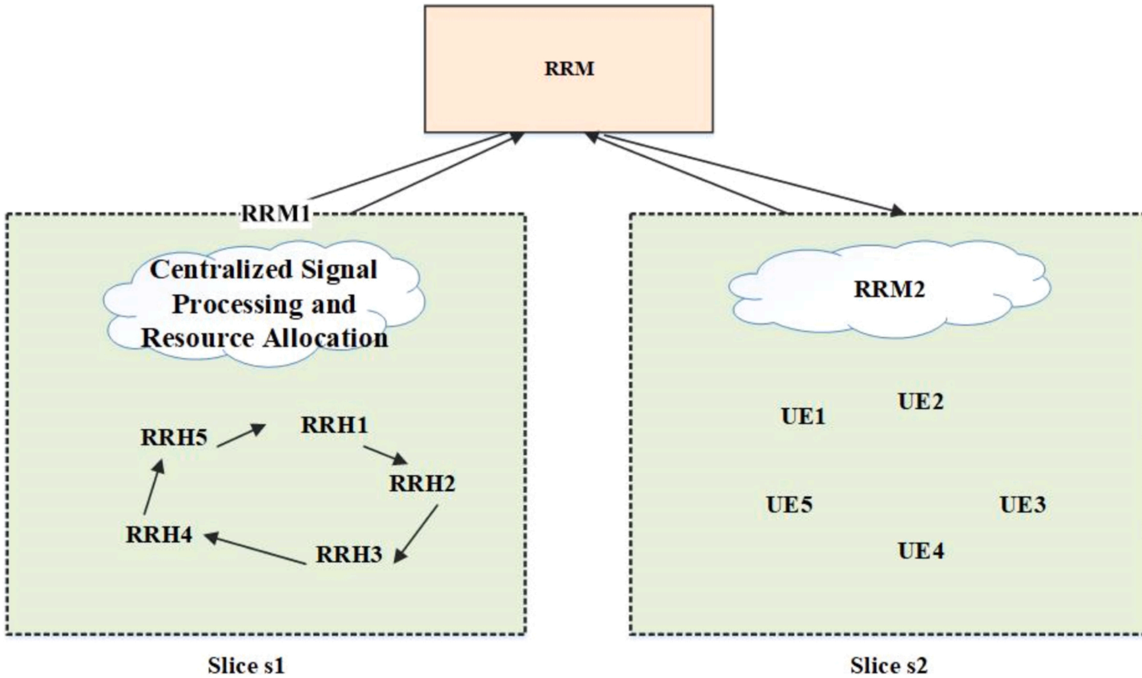

Fig. 2. Hierarchical Resource Allocation.

Here indicate the sample's number and denotes dataset's of element.

To following (7) logarithmic scale to data is applied by logarithmic normalization.

$$\widehat{d} = \log(d) \tag{7}$$

Downlink F-RAN and network slicing

Fig. 2. is downlink F-RAN is made from a single internet, several RRHs, numerous FAPs, and numerous D2D broadcasters. The F-RAN is split into two slices, s1 and s2, with the goals of guaranteeing an excellent data throughput and reducing download delay. Remember that although reducing material downloaded latencies requires using FAPs' buffering capacity, rapid data transmission may be obtained by leveraging consolidated signal conditioning and provisioning of resources in the cloud. As a consequence, slice s1 receives an assortment of thunderstorms and K RRHs, each with M antennas (the set of which is denoted by K = 1, 2,., K). Slice s2 receives P single-antenna FAPs, denoted by the set P = "1, 2,., P". It ought to be noted that but network slicing supports adaptable slice arrangement, infrastructure are provided the settings is typically carried out over an extended duration of duration, and this ought to consider a slice metrics for efficiency and consumers budgets into consideration whereas sub channel utilization is carried out over a shorter period of time for adjusting to the radio atmosphere. The technical design of the slices is set in stone and collaborative transmissions is only used in slice s1 in this paper's study of sub channel assignment for network slicers. The group of UEs having only one antenna that slice s1 and s2 serve should be denoted as Ns1 = 1, 2,., Ns1 and Ns2 = 1, 2,., Ns2 accordingly. Every one of the system's accessible sub channels, given by the notation X = "1, 2,., X," has a bandwidth of Z.

$$w_{ns1,r,x} = \sum\nolimits_{k\in k_{ns1,r}} t^{T}_{ns1,r,k,x} F_{ns1,r,k,x} d \underset{\&}{\&ns1}, r + \sum\nolimits_{ns1,q\in Ns1,q\neq r,k\omega_{ns1,q,k,x>0}} \sum\nolimits_{k\in k_{ns1,q}} t^{T}_{ns1,r,k,x} F_{ns1,q}, k, x d_{ns1,q} + B_{ns1,r}, x \tag{8}$$

A hierarchy radio resource scheduling system with a GRRM also two LRRMs is used to reduce the load from the GRRM while accomplishing slice customization. In particular, the GRRM assigns subchannels onto slicing relying simply on satisfactory feedback provided by LRRMs along with certain imprecise data regarding slices, whereas the LRRM within every segment assigns the given resources to its UEs. This configuration significantly reduces the GRRM's resource distribution problem space, while remaining independent of network bandwidth architecture in each slice. For instance, LRRM 1 may be installed on the potent cloud server cluster, while LRRM 2 could be set up at a FAP with strong compute power and high-quality backhaul connectivity to help gather data about the system from other linked FAPs. Finally, the specified slice management entity may be used to run this GRRM.

The slice S1 model

Each of the UE in slice s1 is deemed as though it has been assigned a subchannel, and that subchannel may be shared by many UEs. The transmitted signal for is represented as (8),

Where $d_{ns1,q}$ is the point of $UE_{ns1,q}$, $c_{ns1,q,k,x}$is a 0–1 indication that becomes 1 whenever RRH k serves $UE_{ns1,q}$ beyond subchannel fulfills set of RRHs i.e., a set of RRHs that serve infers that Subchannel $x, k_{ns1,q}$ has been allocated. Furthermore, $w_{ns1,q,k,x} = 1$ RRH k and is the channel for interacting between on sub channel $UEn_{s1,q\sum_{k} w_{ns1,q,k,x>0}}$, is the RRH k the preceding vector intended for $UEns1, q$, and $b_{ns1,r,x}$the noise that corresponds to the distribution of $WM(0, \sigma^2)$. Afterward, the data rate of is calculated.

The slice S2 model

Concerning slice s2, it expected that each UE is assigned to a single

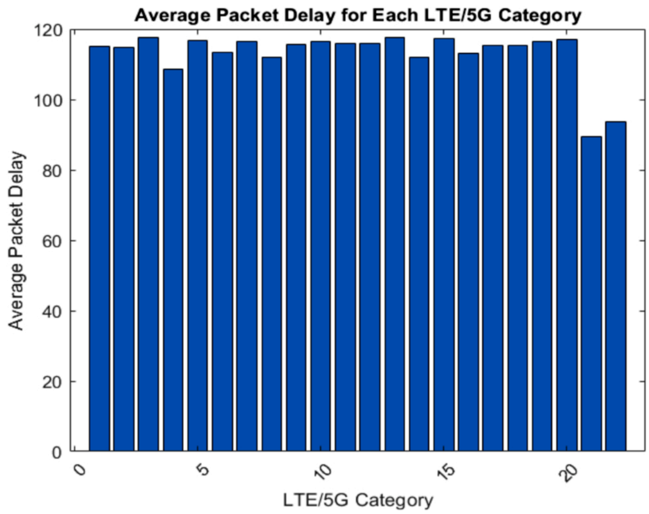

Fig. 3. Average Packet Delay for Each LTE/5 G Category.

subchannel; nevertheless, each subchannel might be shared by numerous UEs retrieving different FAPs. Assume that every FAP chooses common content to be cached and that each in slice s2 randomly requirements a content. The delay caused by retrieving requested materials through the cloud can be avoided if wanted materials are cached at related FAPs. When is served by a FAP p across subchannel x, and its intercepted signal is indicated by (9):

$$w_{ns2,r},p,x = Lpt_{ns2,r},p,xd_{ns2,r} + \sum\nolimits_{ns2,q\in Ns2,x,q\neq r}\sqrt{Lp_{ns2,q}}\,t_{ns2,r,}p_{ns2,q},xd_{n2,q} + b_{ns2,r,x} \tag{9}$$

Wherein is any existing channel gain linking and FAP l throughout sub channel x, lp is the communication to communication of FAP l for each subchannel, believed to be fixed, while is the FAP servicing. Consequently, the transmitting information is provided by (10)

$$J_{ns2,r},p,x = Z\log\left(1+\frac{lp\left|t_{ns2,r},p,x\right|^2}{\sigma^2+\sum\nolimits_{ns2,q\in Ns2,x,q\neq r} lp_{ns2,q}\left|t_{ns2,r},pns2,x\right|^2}\right) \tag{10}$$

The assignment rate of may be expressed with the 0–1 indicator wherein 1 only if and just if it is supplied by FAP p over subchannel x (11).

$$J_{ns2,r}\left(Xs2,\left\{an_{s2,r},p,x\right\}\right) = \sum\nolimits_{x\in X_{s2}}\sum\nolimits_{p\in P} an_{s2,r},p,x. \tag{11}$$

Following that, information download delay is provided by (12)

$$h_{ns2,r}\left(Xs2,\left\{a_{ns2,r},p,x\right\}\right) = \begin{cases} \frac{s_{ns2,r}}{J_{ns2,r}}, whenv_{ns2,r}iscachedatFAPlservingUE_{ns2,r}, \\ \frac{s_{ns2,r}}{J_{ns2,r}}+\beta_{ns2,r}, otherwise, \end{cases} \tag{12}$$

CNN-game theory classification

As effective instruments for pattern detection and data processing, CNNs provide a vital function. CNNs are employed to efficiently interpret and comprehend traffic patterns, user behavior, and dynamic network circumstances. These insights are critical for maximizing resource allocation in next-generation networks, especially when considering network slicing. CNNs assist in accurately identifying network slices and their unique requirements by extracting significant characteristics and patterns from network data. This facilitates the more effective and data-driven distribution of network resources. CNNs play a critical role in accomplishing the goals of effective resource allocation within this advanced networking paradigm because of their data-driven approach, which helps to improve the performance, reliability, and quality of service in next-generation networks.

To achieve improved performance in the current setting, the suggested model's architecture must take use of the synergy between CNN and Game Theory. The design deftly blends the ideas of game theory for strategic decision-making with CNN's potent feature extraction and pattern recognition capabilities. The foundation for processing input

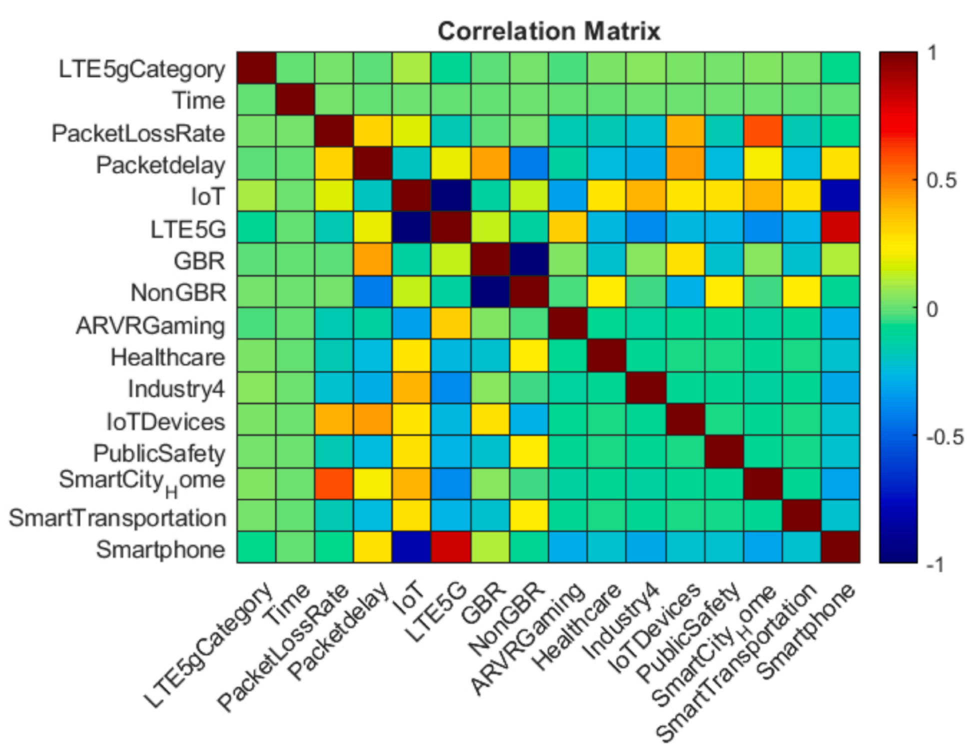

Fig. 4. Correlation Matrix graph.

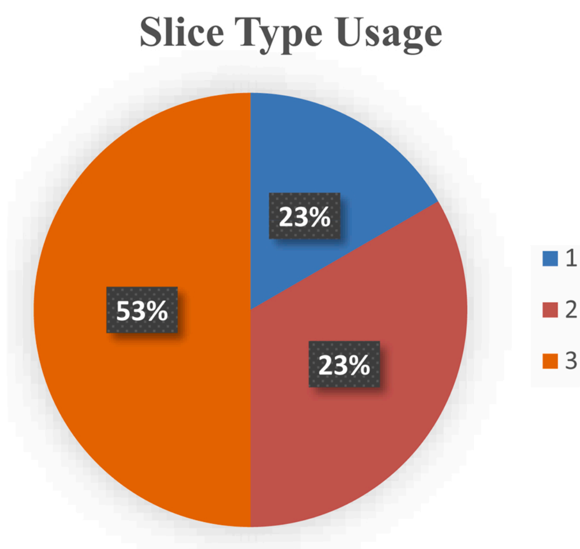

Fig. 5. Slice Type Usage Graph.

data is the CNN component, which efficiently captures hierarchical characteristics and representations required for the current job. In addition, the Game Theory component adds a layer of strategic decision-making where system elements, such network slices or agents, interact in a manner similar to that of a game. Decisions on resource allocation and slicing are influenced by these interactions, guaranteeing a flexible and dynamic strategy. The architecture of the model makes it easier for data to flow between the Game Theory and CNN components, enabling learnt characteristics to influence strategic choices and vice versa. Because of this integration, the model can optimize resource allocation within a game-theoretic framework and adjust to changing network conditions. The model's meticulous symbiotic interaction between CNN and Game Theory components guarantees a reliable and efficient solution for resource allocation in next-generation networks.

VGG-19

VGG-19 has 19 layers, 3 are fully connected, and 16 are convolutional layers. The parameters in deep networks can be reduced by using filters in convolutional layers. This architecture uses a 3 × 3 pixel filter. A maximum pooling layer is used, and there are two steps. There are approximately 138 million calculation parameters in VGG-19.

Because the VGG-19 layer can extract complicated and high-level characteristics from input images, it is an essential part of a CNN's architecture. This 19-layer deep neural network design is well known for its efficiency in image recognition applications. The VGG-19 layer is very helpful for applications like object identification and classification since it is excellent at collecting complex visual patterns, textures, and abstract representations. The VGG-19 architecture gradually refines and abstracts visual characteristics by stacking numerous convolutional and pooling layers, enabling more precise and nuanced image interpretation. Its ability to learn hierarchical representations, which it may use in a range of computer vision applications, makes it a useful tool for jobs requiring a thorough comprehension of visual data.

Path loss

In wireless communication and radio propagation, path loss is the term used to describe the attenuation or weakening of a signal's power

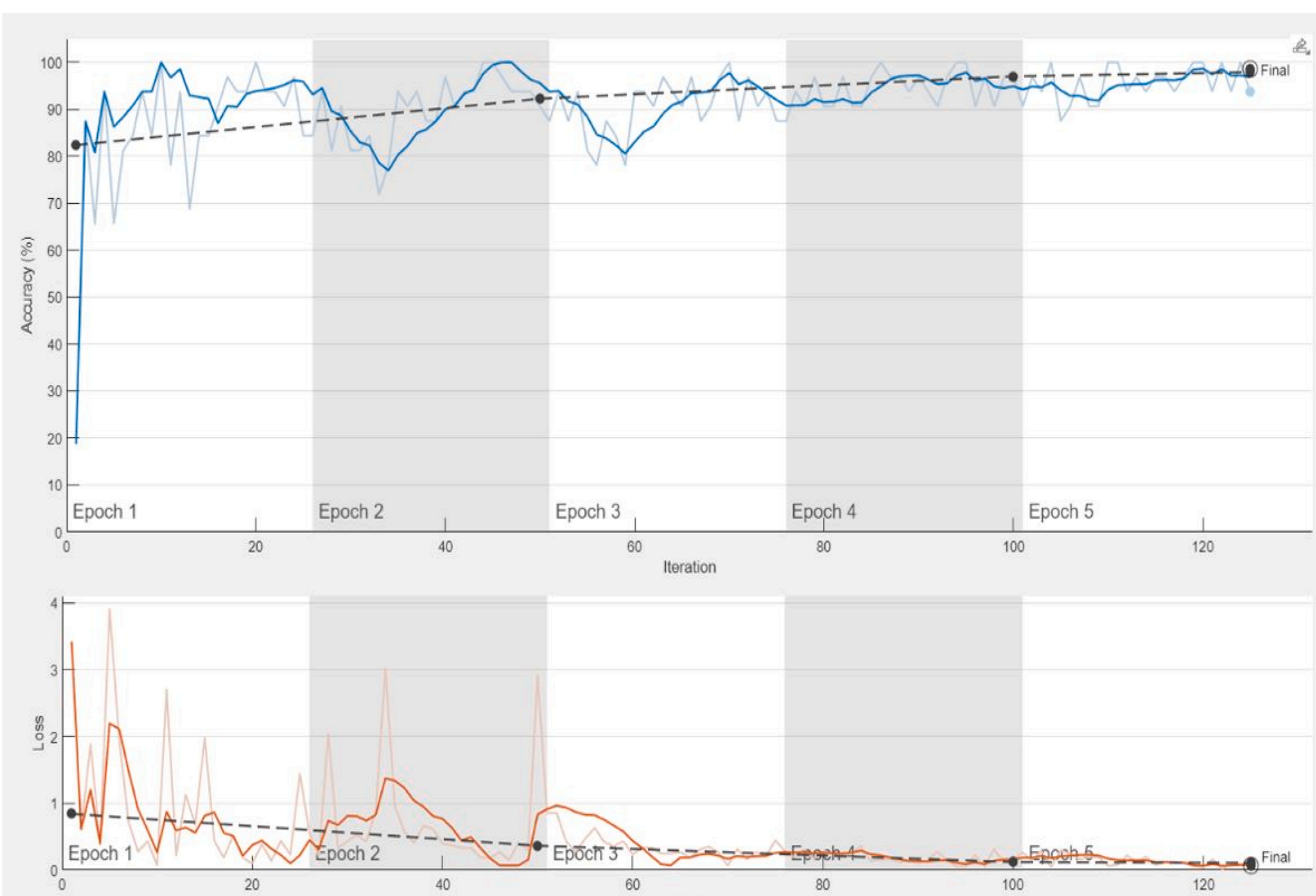

Fig. 6. Training time Accuracy and Loss.

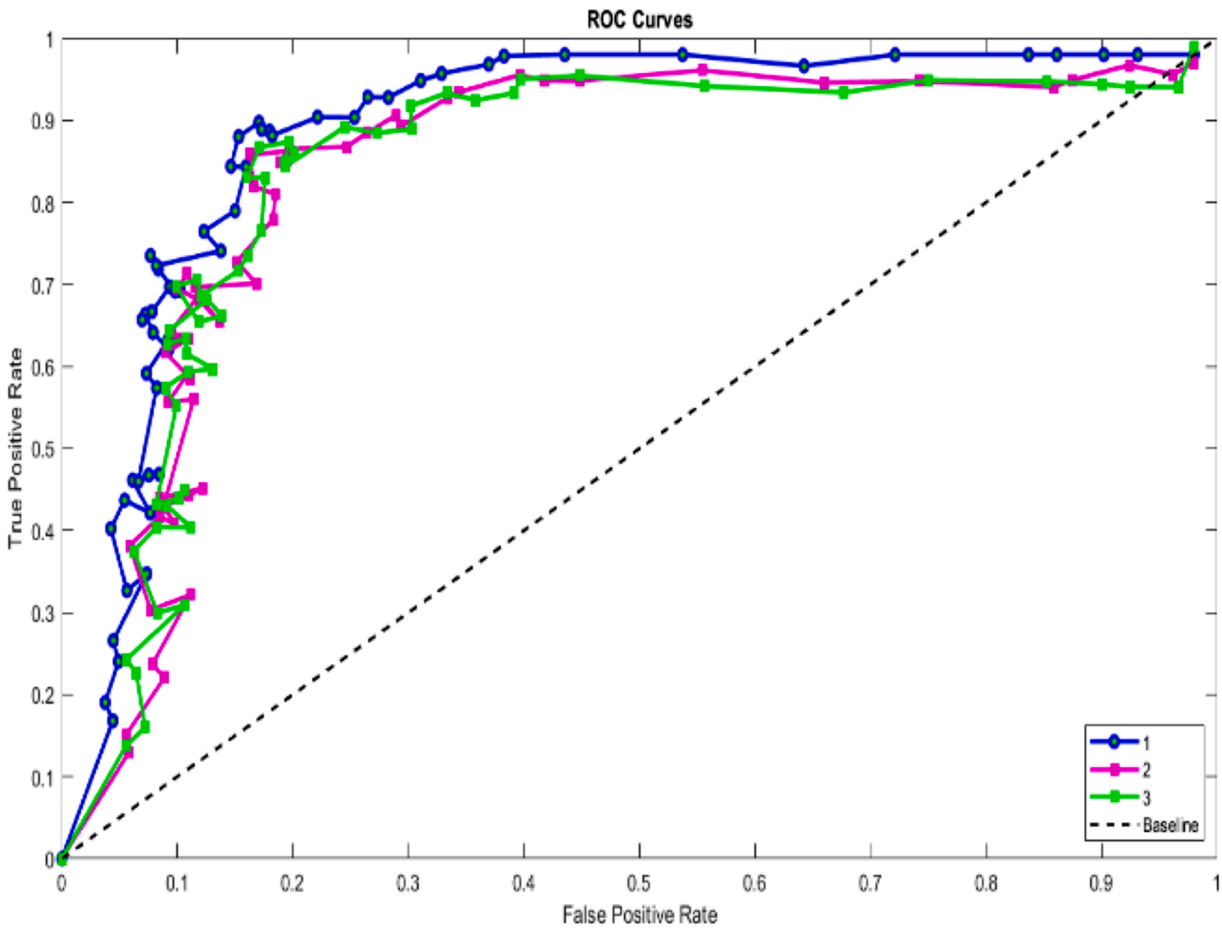

Fig. 7. ROC Curve.

during transmission via a medium, usually air or space. The signal's strength decreases with increasing distance from the transmitter owing to a variety of reasons, including as interference, impediments, and distance. Since route loss phenomena directly impacts signal coverage, range, and overall system performance, it is an essential factor to take into account while planning and optimizing wireless networks. In order to predict and account for path loss, engineers and researchers use mathematical models and empirical measurements. This enables them to determine the necessary transmit power, antenna placement, and other parameters for achieving dependable and effective wireless communication in a variety of scenarios and environments.

Determine path-loss modeling across a big region in order to build equipment and generate a database. Applying the data from the collection and the linear-fit connection derived from slice s1 with slice s2 model operations, two route loss scenarios were built. After determining the connection their distance, the path-loss modeling was estimated using the curve-fitting method. However, the s1, and s2 functions were chosen, resulting in the development of the MATLAB curve fitting tool for estimating correlations and separation (13).

$$fitness = MAE = \frac{1}{m}\sum\nolimits_{q=1}^{m} |l_q - r_q| \tag{13}$$

Game theory for optimize the weights

Iterative bargaining model-based routing for changing VNs was presented to alleviate the drawback of a typical bargaining game that misses comprehensive information. Modelling the game as given (14),

$$G_T = \{P, R, \{U_1, U_2, \dots, U_n\}\} \tag{14}$$

Where P indicates the overall number of competitors, R denotes the methods used for selecting the relay vehicle, and Uj means the usefulness of player j, which is calculated by transforming the breakdown of the time and activities taken into the amount of contentment experienced by the player and is stated in (15).

$$U_j(R_j(t), t) = \int_0^t U_j(R_j(t))dt \cong \sum_{n=0}^{n=t} U_j(R_j(n)) \tag{15}$$

Where $R_j(t)$ represents plan of player j at period t. The vehicle j chooses the most flexible relay having the least connection cost PCj that could include expanded information. By employing the successive bargaining game to make iterative decisions, the most flexible path and nodes for

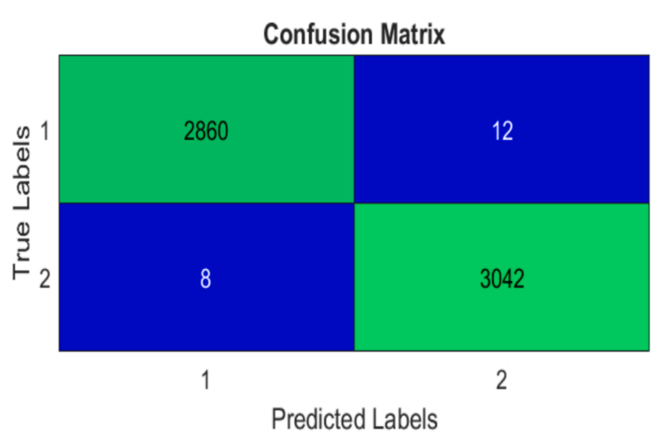

Fig. 8. Confusion Matrix of Network Slicing Recognition Dataset.

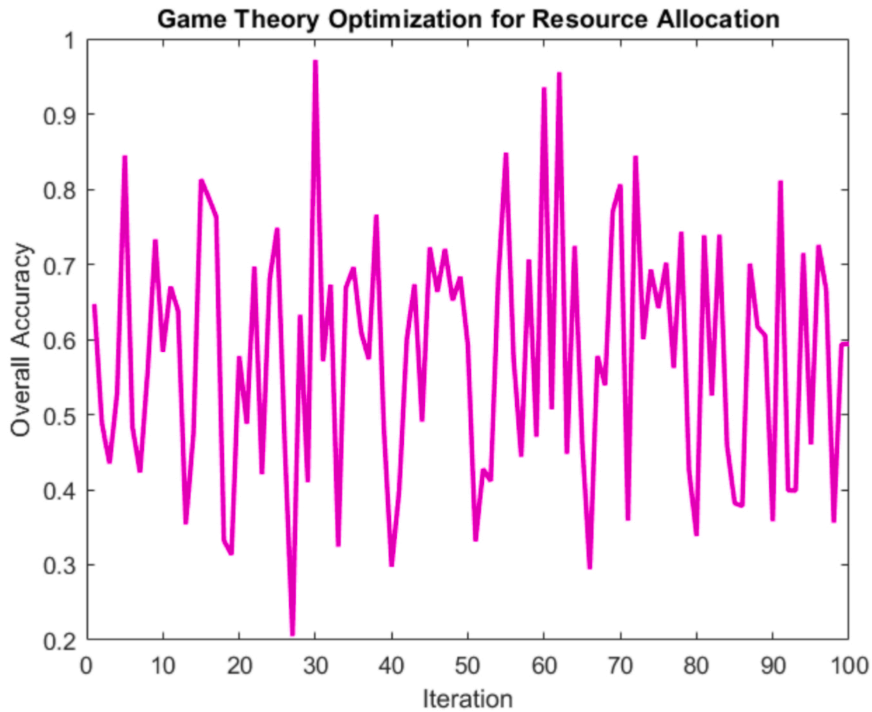

Fig. 9. Overall Accuracy in Game Theory Optimization for Resource Allocation.

relay may be chosen. Particularly, the receiver vehicle chooses the most flexible route path Rp. (16)

$$R_p = \min_{\{P_j \epsilon S\}} \int_{t=T_s}^{t=T_e} \log(L - P_j)\, dt \quad (16)$$

Pj represents the jth distribution path between the starting vehicle and target vehicle, and S is the collection of developed routing pathway in this scenario. The starting point for package delivery is specified by Ts, and a packet forward ending time by Te. By converting the conventional bargain game to a periodic recurrent bargaining method, this routing strategy solves the traditional bargaining game's problem of missing complete information. Whenever the most adaptable intermediaries are chosen, the most adaptable multi-hop connection is built by repeatedly forwarding the projected route cost.

The study's investigation technique would be closely aligned with the simulation setup and parameters. A typical simulation setup for this kind of research would entail modelling the behavior of next-generation networks using the network simulation programme. Network topology, user equipment models, communication protocols, traffic patterns, and different network slicing configurations would all be included in the parameters. Training and testing datasets for the CNN-based recognition model would be needed; these datasets might be created artificially or based on actual data. The particular game-theoretic models that are applied to resource allocation will determine the parameters of that theory. It is probable that the research will establish and test several performance measures, such latency, packet loss rate, and resource use, in order to assess how effective the resource allocation strategy is.

Algorithm 1. : CNN-Game Theory.

Data Preparation
Load and prepare the data for network slicing
Divide the data into sets for testing and training
CNN Training
Set up and initialize the CNN model in order to extract features
Put together the model using a suitable optimizer and loss function
Utilize the training data to teach the CNN
To avoid over fitting, validate the model using a validation set
Game Theory-Based Resource Allocation Setup
Describe the framework for resource allocation using game theory
Name the participants, tactics, rewards, and utility function
Set the game's current state to initial
Iterative Process of CNN and Game Theory Integration
CNN Feature Extraction
Game Theory Decision-Making
Update Game State
CNN Fine-Tuning
Step 5: Evaluation and Testing
Analyze the integrated model using the testing set.
Create ROC curves and compute AUC to evaluate the effectiveness of recognition.
Resource Allocation in Next-Generation Networks
Apply the network slices' optimal resource allocation techniques
Using data from real-time monitoring, adjust resource allocation dynamically

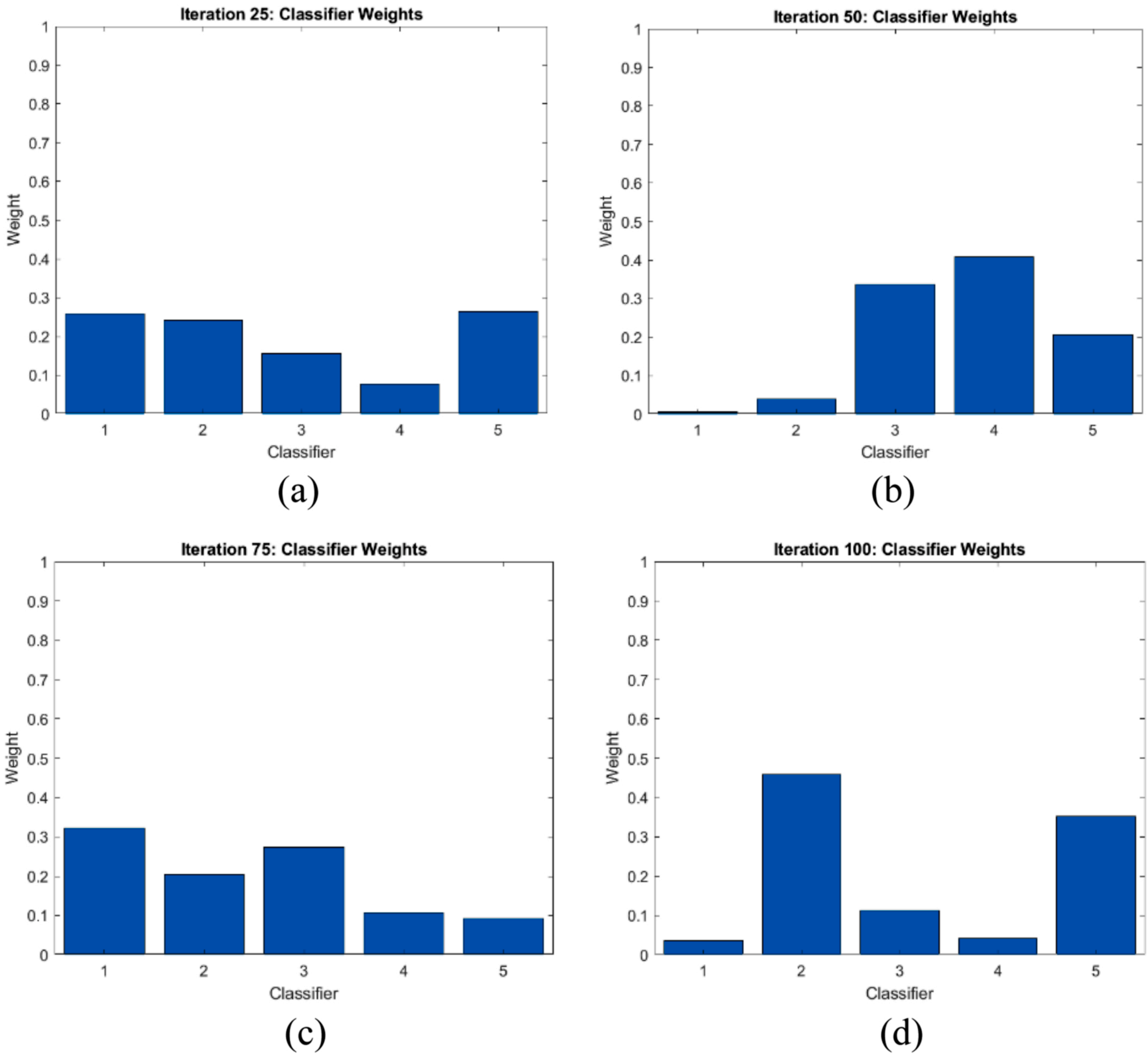

Fig. 10. Classifier Weight for Various Iteration (a) Iteration 25 (b) Iteration 50 (c) Iteration 75 (d) Iteration 100.

Initial data must be loaded and arranged into training and testing sets in order to prepare the data for network slicing. Next, using the proper optimizer and loss function, a CNN is trained to extract features from the prepared data. Concurrently, a framework grounded on game theory is developed for allocating resources, delineating players, tactics, incentives, and the utility function. Game theory and CNN are integrated iteratively through the extraction of features using CNN, the allocation of resources based on game theory, and the subsequent update of the game state. Furthermore, CNN fine-tuning may be applied in response to these choices. ROC curves and AUC computations are used in the assessment and testing process to evaluate the integrated model's performance. In order to guarantee effective resource allocation in Next-Generation Networks, the optimized resource allocation algorithms are then applied to network slices, with dynamic modifications based on real-time monitoring data.

Table 2
Comparison of Performance Metrics.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RNN [29]	94.23	94.11	96.45	94.78
DeepCog [30]	97.87	93.78	95.23	97
DHOA [31]	92.88	89.88	92.54	92.67
CNN-LSTM [32]	94.11	92.67	95.68	93.54
Proposed CNN-Game Theory	98	97.55	97.11	97.98

Results and discussion

The novel aspect of this research lies in the innovative combination of Convolutional Neural Networks and Game Theory principles, which has not been traditionally used in the context of resource allocation in Open RANs. The unique use of Game Theory to optimize the classifier weights post-CNN classification sets a precedent for future studies in this domain. Moreover, the hybrid model allows for a more dynamic,

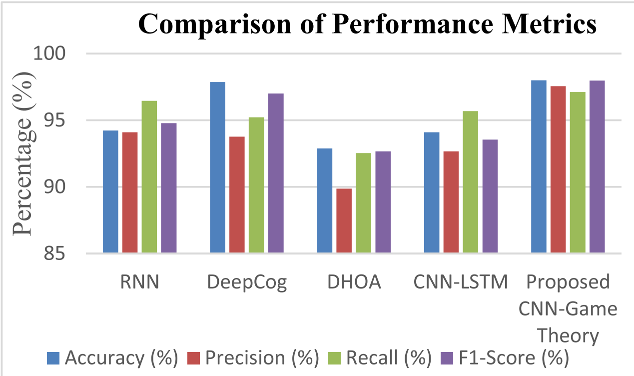

Fig. 11. Comparison of Performance Metrics.

adaptable, and efficient management of network resources, showcasing a significant potential for implementation in diverse and complex network environments. MATLAB 202 is used to simulate the suggested localization procedure. The novel aspect of this research lies in the innovative combination of Convolutional Neural Networks and Game Theory principles, which has not been traditionally used in the context of resource allocation in Open RANs.

The above Fig. 3. Showcases the comparative performance of various LTE/5 G categories concerning packet delay, providing valuable insights into the efficiency and responsiveness of each category's network for data transmission. Understanding these delays is crucial for network operators and researchers to optimize network performance and enhance user experiences based on their specific requirements.

Above Fig. 4 provides a visual representation of the relationships between various variables in the LTE/5 G network context. The matrix likely shows correlation coefficients between LTE5g category, time, packet loss rate, and packet delay, as well as other factors like IoT, GBR (Guaranteed Bit Rate), nonGBR, ARVR gaming, health care, industry 4, IoT devices, public safety, smart city, smart transportation, and smart phone. The graph enables researchers to identify potential dependencies and associations between these factors, aiding in the understanding of network performance and potential implications for different applications and services.

Above Fig. 5. shows the usage distribution of different network slices is displayed. The blue segment represents 53 % of the total slices, indicating the dominant slice type. The yellow and green segments, accounting for 23 % each, represent the secondary slice types. This visual representation provides valuable insights into how network resources are allocated among various slice types, enabling researchers and network operators to optimize resource provisioning and enhance network performance for different service requirements.

Above Fig. 6. shows the training time, accuracy, and loss metrics are displayed. The x-axis likely represents the different training iterations or epochs, while the y-axes represent the corresponding values for accuracy and loss. The graph allows researchers to observe the trends in accuracy improvement and loss reduction over training time, providing valuable insights into the model's learning behavior and convergence for potential optimization and comparison purposes.

Above Fig. 7. shows ROC curve the trade-off between sensitivity and specificity, helping researchers assess the model's ability to discriminate between different classes and determine the optimal threshold for classification decisions. A higher area under the ROC curve indicates better model performance and discrimination ability. In the framework of Efficient Resource Allocation using CNN-Game Theory Based Network Slicing Recognition for Next-Generation Networks, the ROC curve is important. This novel method uses the ROC curve as a performance assessment tool to show how different threshold settings for network slicing identification affect true positive rates and false positive rates. When CNNs are utilized for effective feature extraction and resource allocation choices are made based on Game Theory concepts, the ROC curve offers information about how well the model can differentiate across different network slicing categories. The area under the curve and its shape provide information on the discriminating strength of the algorithm, which helps optimize the recognition system's resource allocation. This framework's use of ROC analysis emphasizes how important it is to assess and optimize CNN-Game Theory model performance in the intricate world of Next-Generation Networks in order to distribute resources fairly and effectively across various network slices.

Usually, a benchmark is shown by the diagonal line, also known as the no-discrimination or random guess line. On the ROC plot, this diagonal line joins the points (0,0) and (1,1). Stated differently, a model whose predictions align with the diagonal is as good as chance. Whether it's a classification algorithm or another kind of model, the objective of a predictive model is to beat this benchmark. This diagonal line is the reference point for the ROC curve that a model produces, and the area under the ROC curve (AUC) is a widely used measure to assess the discriminatory power of the model. Better performance is indicated by an AUC value nearer 1, whereas performance that is comparable to random chance is suggested by an AUC value around 0.5. In conclusion, the benchmark in ROC curve analysis offers a standard by which to measure how well the model predicts the future.

The above Fig. 8. Provides a comprehensive assessment of the classification model's performance. The matrix displays the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions for each network slicing category. This visual representation enables researchers to evaluate the model's accuracy, precision, recall, and F1-score, offering valuable insights into the model's capability to correctly identify and distinguish different network slicing categories.

The above Fig. 9. depicts the performance of the proposed game theory-based resource allocation method. The x-axis likely represents different experimental scenarios or iterations, while the y-axis represents the overall accuracy achieved by the optimization model.

This graph provides a visual overview of how well the game theory approach allocates resources, enabling researchers to assess its effectiveness and compare it with other resource allocation strategies in the context of game theory optimization.

Above Fig. 10. illustrates the evolution of classifier weights over different iterations during the model training process. The subplots (a), (b), (c), and (d) represent the classifier weights at specific iterations: (a) Iteration 25, (b) Iteration 50, (c) Iteration 75, and (d) Iteration 100.

Each subplot likely shows the weights assigned to various features or variables in the classification model. This visualization allows researchers to observe how the model's learning progresses over iterations and identify the importance and influence of different features on the classification task at different stages of training.

A thorough comparison of performance measures for the different research techniques is shown in Table 2. The metrics Accuracy, Precision, Recall, and F1-Scoreoffer a comprehensive image of each method's efficacy in relation to the given task. All measures show that the Recurrent Neural Network (RNN) performs well, with recall being its strongest suit. High accuracy and an F1-Score demonstrate DeepCog's proficiency in both overall categorization and precision-recall balancing. The DHOA approach maintains a balanced performance across precision, recall, and F1-Score, but having a slightly lower total accuracy. Consistently demonstrating competitive results in accuracy and precision-recall measures, the CNN-LSTM hybrid works well. Especially, the suggested CNN-Game Theory approach performs better than any other, with an astounding 98 % accuracy and exhibiting greater F1-Score percentages, recall, and precision. This indicates that the suggested approach's incorporation of Game Theory and CNN improves overall classification performance, highlighting the potential effectiveness of this innovative technique. In Fig. 11, it is illustrated.

Discussion

The findings highlight how well the different research approaches performed, and they have important ramifications for the current job. Strong recall is demonstrated by the RNN [29], demonstrating its efficiency in accurately detecting pertinent events. DeepCog exhibits strong accuracy and a sensible trade-off between precision and recall, proving its prowess in general categorization tasks. The precision, recall, and F1-Score measures are all balanced even with the somewhat reduced accuracy of the DHOA approach [31]. The CNN-LSTM hybrid performs consistently and competitively in a number of criteria [32]. The suggested CNN-Game Theory technique is particularly effective compared to the other methods; it achieves an astonishing 98 % accuracy and shows higher precision, recall, and F1-Score percentages. This shows that the suggested approach's incorporation of CNN and Game Theory improves overall classification performance, demonstrating it's potential as a cutting-edge and successful technique for the particular task examined in the study. The suggested method's strong performance indicates that it is appropriate for situations where balanced precision-recall performance and high accuracy are crucial.

Conclusion and future scope

In conclusion, this research paper presents an organizational radio resource distribution architecture for reconfigurable wireless connection slicing in next-generation networks. The proposed architecture addresses the challenges posed by the growing number of Users Equipment's (UEs) and the strain on radio resource management (RRM) in centrally controlled network slicers. By introducing neighborhood radio resource managers (LRRMs) responsible for subchannel distribution within slices, the approach enables efficient slice customization and improved quality of service (QoS) for 5G and 6G networks. Additionally, the paper introduces CNN-Game theory-based network, a unique technique for maximizing weights in neural networks through game theory principles. The approach leads to enhanced accuracy and efficiency in neural network models, demonstrating its potential for improving various machine learning applications. The experimental outcomes showcase impressive performance with a high overall accuracy value of 98 % in the context of game optimization for resource allocation. These findings emphasize the significance of the proposed approach in meeting the stringent requirements of next-generation networks, ensuring extreme safety, minimal latency, reliability, and bandwidth. Overall, research contributes valuable insights into efficient resource management and weight optimization techniques for advanced wireless networks and machine learning applications. The future scope of this research article lies in exploring and expanding the proposed organizational radio resource distribution architecture and CNN-Game theory-based network technique in various aspects of next-generation networks and machine learning applications. The restricted adaptability of Efficient Resource Allocation by CNN-Game Theory Based Network Slicing Recognition for Next-Generation Networks might result in less-than-ideal resource allocation as it relates to dynamic and unexpected network settings. In order to improve resource allocation efficiency, future research can integrate real-time data and adaptive algorithms; use machine learning models with real-time network performance data; apply reinforcement learning to adaptive resource allocation; and leverage edge computing and edge AI to make decisions in evolving next-generation networks more responsive and latency-free.

Ethical approval

Not applicable. The work presented in this manuscript is mathematical modelling only for efficient resource allocation through CNN-game theory-based network slicing recognition for next-generation networks. No experiment was performed on the human body and living organism/animal. So, ethical approval from an ethical committee is not required.

Authors contribution

Dr. Franciskus Antonius was solely responsible for conceiving the research idea, conducting all experiments, gathering and analyzing data, and writing the entire manuscript.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The study efficient resource allocation through CNN-Game theory-based network slicing recognition for next-generation networks employed a network slicing recognition dataset that was sourced from Kaggle, a well-known platform for sharing and accessing datasets-https://www.kaggle.com/datasets/gauravduttakiit/network-slicing-recognition.

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The authors would like to acknowledge that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

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