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Analysis of AI-Driven Modulation for Cognitive Cellular Networks : DNN Approach

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Abstract : *Objective: analyze the modulation scheme that can intelligently select the appropriate modulation model for service conditions to obtain a high Signal to Noise Ratio, as well as throughput efficiency on wireless networks through the DNN approach. Method: this study uses simulations with the Python language, through AI-Driven on BPSK, QPSK, 16-QAM, and 64-QAM modulation, to determine the SNR and Quality of Service (QoS) produced, both through conventional approaches and Deep Neuro Network (DNN). Researh Finding: AI-Driven modulation used for Cognitive Cellular Networks (CCN), through Deep Neuro Network designed to intelligently classify and select the appropriate modulation model to be applied, shows significant improvement in throughput efficiency, QoS and has the ability to adapt to the environment in dynamic networks. Conclussion: AI-Driven using Deep Neuro Network is able to dynamically adapt to determine the selected modulation model, according to the user's environmental conditions, increase spectrum efficiency and throughput, and increase SNR which can automatically increase the efficiency of network usage.*

Keywords: *AI-Driven, Cognitive Cellular Network, Deep Neuro Network, Modulation*

1. INTRODUCTION

Human mobility is increasing in the modern day, necessitating a variety of speedier and more varied information and telecommunication services and applications to keep life moving along. Naturally, wireless telecommunication networks must be able to meet this requirement. To do this, traditional cellular networks have evolved into cognitive cellular networks, which use cognitive technology to increase the flexibility and efficiency of frequency spectrum usage, making them more dynamic and able to optimize user performance and service quality.

The field circumstances for the rapidly evolving 5G cellular network include noise, multipath fading, and interference, which frequently impact signals in cellular networks and make modulation decisions challenging. In actuality, apps and user services should be able to provide a high-throughput, real-time communication process. This undoubtedly has a significant impact on the modulation scheme that is chosen. Because conventional modulation schemes, like Phase Shift Keying (PSK) or Quadrature Amplitude Modulation (QAM), frequently rely on rigid models or heuristic-based algorithms, they struggle to handle complex dynamics and can't react in real time to changes in the environment.

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According to Frank and Marcos (2007), the Cognitive Cellular Network is a wireless system that makes use of artificial intelligence (AI) to make judgments on how to operate in order to give users the best experience possible.

It is challenging to represent modulation optimization using linear techniques because it involves intricate connections between factors like SNR, transmission power, and interference. In order to create a dependable, real-time communication and information system that can manage the massive amounts of data produced by contemporary networks and use the information already in place to choose a more accurate modulation scheme, Deep Neural Networks (DNNs) are employed.

According to Gopinath et al. (2023), a DNN is an artificial neural network that has several layers between the input and output layers. Neural networks built with perceptrons, HNNs, and other methods use the concept of a single input layer and a single output layer, claim Mohanasundaram et al. (2019). Meanwhile, more than three input or output layers are considered to be a deep neural network.

The number of hidden layers is the primary distinction between deep neural networks and regular neural networks. Deep neural networks have several hidden layers, whereas conventional neural networks only have one or two (Subasi, 2020).

Deep Neural Network (DNN) can be a solution to realize a reliable communication and information system. However, it is necessary to further study how Deep Neural Networks (DNN) can be used to dynamically classify and adjust modulation schemes in cognitive-based cellular networks. How effective is the DNN approach compared to traditional methods in optimizing spectrum efficiency and reducing interference in CCN. It is also necessary to study how to determine an efficient DNN architecture design to be implemented in real-time on devices in cellular networks and the integration of DNN-based modulation schemes with multi-parameter management in Cognitive Cellular Networks to realize optimal network performance.

2. LITERATUR REVIEW

Human life is increasingly complex and dynamic, demanding the availability of a network that is able to accommodate all the needs of human activities. Mariscal et al in his research about deep learning applications of cognitive network, 2022 stated that currently a telecommunications network is needed that is able to transmit all data between various conditions and environmental components, as in Figure 1 below.

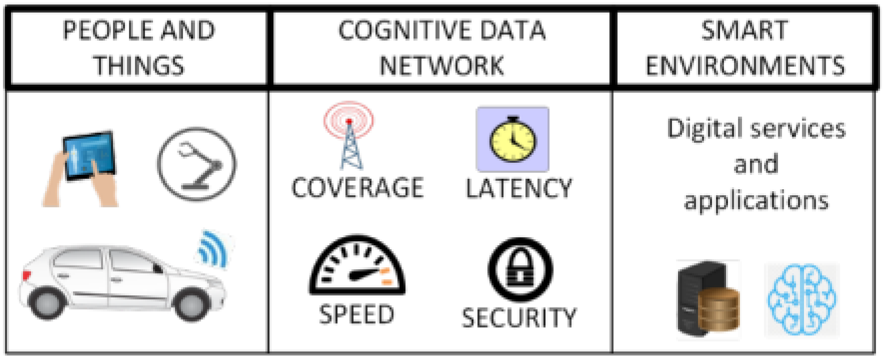

Figure 1. Environmental conditions connected in cognitive data network

Source: Mariscal et all, 2022

Without the availability of a network equipped with intelligence and the ability to adapt quickly, precisely and dynamically, it will hinder the formation of telecommunications, especially failure in real-time communication functions.

Cognitive Cellular Networks are the focus of intensive research, because of their ability to support various services, which require extreme connectivity performance. The implementation of increasingly broad and diverse digital services requires increasingly sophisticated network management and is able to minimize human involvement in its operation. Therefore, a smarter network is needed, as is commonly referred to as a cognitive network or artificial intelligence (AI) including machine learning and machine reasoning, adaptive knowledge and data management.

Malik et all (2015) in their research on QoS in wireless networks stated that Cognitive cellular networks (CCN) are a wireless generation that uses artificial intelligence (AI) to improve network performance and reduce human intervention. CCN uses cognitive radio (CR) and cognitive engines to sense, reason, and act autonomously, including Sensing activities (CCN can find out and collect data on power, frequency, and interference levels in certain conditions), Reasoning (CCN) can use knowledge reasoning and optimization to learn from experience in previous conditions and decide on selected activities), Acting autonomously (CCN can act autonomously and always optimize performance) (Zaheer et all, 2024).

Raju et all (2017) explained that CCN is designed to be able to determine solutions to the complexity of wireless network and media parameters, so that it can overcome spectrum availability, by automatically adapting to changes in user application requirements, its ability to provide quality of service, self-management without human intervention, and providing flexibility in opportunistic network access.

However, Salvi et al. (2021) clarified that a deep neural network (DNN) is an artificial neural network that processes input by utilizing multiple intricate layers.

In line with what was conveyed by Nayeri et all (2021) and Salvi et all (2021), that DNN has a structure with many input and output layers, including hidden layers that store information about the importance of input. DNN uses intelligent mathematical modeling to learn complex models and improve the accuracy of machine learning models. In its implementation, DNN is used in many fields, including computer vision, language processing, transfer learning, carrying out tasks such as voice command recognition, image recognition, and caption writing.

Deep Neural Networks (DNNs) are extremely sophisticated machine learning systems that can stack multiple layers of neural network models at once, according to Soni et al. (2022). Through the processing of input on one layer and output on the subsequent layer, this network links neurons to answer intricate mathematical problems. Thus, it may be said that the Deep Neural Network concept mimics the way the human brain functions. The neural network is made up of a number of algorithms that are modeled after the structure of the human brain. The technology's goal is to replicate human brain function, particularly when it comes to pattern recognition and information transfer between different neural connection layers.

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The "feature hierarchy" is the method by which each of these tiers carries out particular kinds of sorting and categorization. Neural networks, like the human brain, are made up of a number of data points that are either directly input by programmers or gathered by sensors. Images, text, or audio that has been transformed into numerical form can all be used as data.

To finish a task or make a forecast, the various data from the input and output layers must be processed step-by-step. After receiving the data, the network's first layer computes an activation function to produce a result, which may be a probability prediction. The following layer of neurons then receives this outcome. In order to arrive at the final result, the relationship between two successive layers is linked to "weights" that establish the impact of the data on the outcomes generated by the subsequent layer. Unstructured data processing is one use for deep neural networks. In addition to automating certain human labor jobs, neural networks with the DNN structure may classify data stored in databases and organize data without labels or frameworks. This is utilized for facial recognition technologies in the realm of video surveillance. This technology is also necessary for autonomous vehicles. This also applies to recommendation engines on Netflix, Spotify, and Amazon, as well as virtual assistants like Siri and Alexa. Therefore, you can be utilizing deep neural network-based goods on a daily basis without even realizing it.

According to Shehzad et al. (2021), a DNN is made up of several neurons grouped in specific layers. Figure 2 generally depicts the DNN architecture with two hidden layers. After receiving input and applying a function—typically non-linear—each unit forwards the output to the subsequent layer.

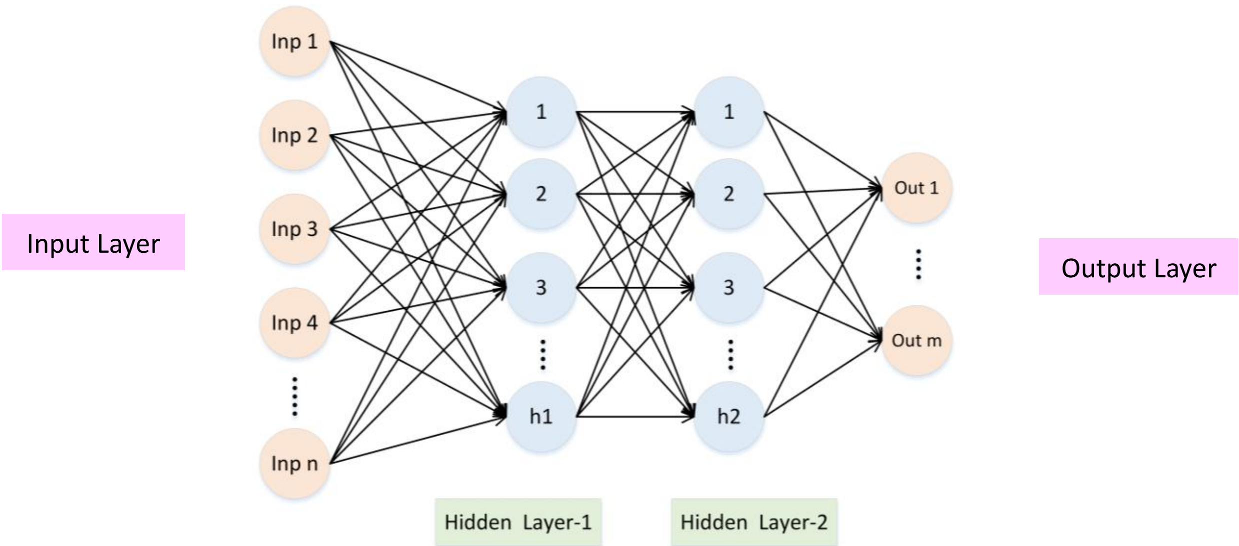

Figure 2. Deep Neural Network Architecture with Two Hidden Layers

Source: Shehzad et all (2021)

The DNN model in Figure 2 is a general model containing n input nodes with hidden layers are h1 and h2, and m output layers.

5G as a rapidly growing cellular network currently accompanied by a very rapid increase in users demands the availability of increasingly large, complex and increasingly intelligent data transmission (Chen et all, 2017). However, limited network availability, layered protocol architecture resulting in limited network capabilities in adapting to the environment causes suboptimal telecommunications performance. In order to overcome this obstacle, Lewis (2016) in his book entitled Deep Learning Made Easy with R: A Gentle Introduction for Data Science conveys the power of the human brain which is formed from millions of neurons, which can work in parallel by processing memory and information received to be distributed through neural networks. This serves as the foundation for creating artificial neural networks, which are collections of nerve components that can adapt, are hierarchically well-organized, and can be connected in parallel to interact with objects in the real world similarly to how the human nervous system does. According to Lewis, DNN is a generalization of artificial neural networks (ANN) that employs multiple hidden layers, meaning that more neurons are used by employing a stack of processing layers, where each succeeding layer learns data representations with different degrees of abstraction and information by using the output of the preceding layer as input.

Additionally, according to Mariscal et al. (2022), the use of deep learning algorithms can enhance cognitive networks' capacities to optimize network performance by enabling protocols to monitor network conditions and leverage past knowledge to effectively respond to intricate and dynamic operations. DNN can manage data created by increasingly heterogeneous mobile environments, which are typically acquired from several sources, have varied formats, and exhibit complicated correlations, according to a survey by Zang et al. (2019). As a result, Cognitive Cellular Networks require the implementation of an adaptive modulation scheme, particularly for optimal quality of service and spectrum efficiency. It enables the system to dynamically choose the best modulation scheme depending on shifting channel circumstances and communication contexts, particularly in networks integrated with Deep Neural Networks (DNN). When using Deep Neural Networks to Cognitive Cellular Networks, selecting the appropriate modulation scheme is crucial for obtaining precise signals during the modulation and demodulation operations. According to a study by Liu et al. (2017), the DNN architecture can classify wireless signal modulation with high accuracy.

3. METHOD

Automated modulation categorization (AMC), according to Yilmaz and Pusane (2020), has numerous applications in cellular communications since it can recognize modulation schemes without requiring prior knowledge of signal properties. By preventing the transmission of feedback bits or needless extra modulation information bits in each symbol header, AMC contributes to link adaptation in cellular communication systems that strive to maximize spectrum efficiency. Chen et all (2020) in real-time conditions, users are likely to receive signals simultaneously due to the large number of transceiver antennas used. Therefore, adaptive coding and modulation are needed to minimize the occurrence of signal quality degradation due to multipath fading.

To maintain the target block error rate, the transceiver uses adaptive coding and modulation methods to change its modulation type based on the channel conditions. Users will simultaneously receive signals from many transmitters in the fifth generation (5G) communication system, as is to be expected in the next generation communication system due to the huge number of multiple antennas. Furthermore, unmanned aerial vehicles (UAVs) in 5G and later systems get information from various sources and pathways, which causes multipath fading to deteriorate the signal quality. This makes it challenging to detect the signal in real time. Thus, the largest issue is to identify and classify modulation kinds in real time at the receiver. Thus, for accurate signal identification and classification in 5G and future systems, AMC is crucial (Zhang et al., 2018).

According to Dileep et al. (2020) at the National Conference on Communications, baud rate, number of symbols, and sampling rate are some of the elements that have a significant impact on analog and digital modulation. The transmitter must be aware of the modulation used based on two requirements: the broadcast of modulation information in each symbol header, which causes overhead and spectrum waste, and the channel condition, which the receiver must know beforehand for correct demodulation.

To improve the accuracy of modulation system usage and spectral efficiency, this study uses AI-Driven which can detect receiver modulation schemes adaptively and in real-time.

At this stage, the dataset used can be a simulation of cellular network conditions with various SNR and QoS values that will be analyzed by DNN. Methods used in this study focuses on:

- Deep Neural Networks (DNN): Using DNN models to predict and select the most efficient modulation scheme based on network variables such as SNR, interference, and channel conditions.
- Cognitive Radio: Applying cognitive radio concepts for dynamic spectrum adaptation.
- The process of choosing the best modulation scheme based on the available SNR conditions involves evaluating several schemes, including BPSK, QPSK, 16-QAM, 64-QAM, and others, using DNN

The idea behind AI-Driven Modulation for Cognitive Cellular Networks is to optimize the choice and modification of modulation schemes in intelligent cellular networks by utilizing artificial intelligence, more especially machine learning and deep learning techniques. By adapting communication operations to shifting environmental conditions, such as interference levels and signal quality, cognitive cellular networks aim to increase the efficiency of limited radio spectrum usage.

Cognitive cellular networks are networks that can adapt to dynamic communication channel conditions. This system utilizes Cognitive Radio technology, which allows the network to monitor the frequency spectrum conditions in real-time and select the best spectrum or channel for communication without disturbing other systems using the spectrum. In this regard, modulation is one of the key elements of a communication system that guarantees the most efficient transmission of data.

In cellular networks, modulation is a method for transforming digital signals into analog signals that can travel via a communication channel. BPSK (Binary Phase Shift Keying), QPSK (Quadrature Phase Shift Keying), QAM (Quadrature Amplitude Modulation), and other modulation methods are frequently employed in cellular communications. The channel conditions, particularly the signal-to-noise ratio (SNR), have a significant impact on the choice of modulation scheme. In low SNR situations, lower modulations like BPSK and QPSK are utilized to preserve signal stability and minimize transmission mistakes. When the signal-to-noise ratio (SNR) is high, stronger modulations like 16-QAM or 64-QAM are employed because they can send more bits per symbol, which boosts throughput. Artificial intelligence (AI)-based methods, particularly Deep Learning and Reinforcement Learning, provide advanced methods for forecasting channel conditions and choosing the best modulation schemes. AI enables systems to anticipate better outcomes based on evolving network conditions and learn from past data.

Deep Neural Networks (DNN) are one of the most widely used AI applications in cognitive cellular networks. Based on a number of factors, including SNR, signal quality, and interference, DNN can identify patterns in large data and forecast the best modulation scheme choice.

Performance Analysis with SNR and QoS

The two primary metrics used to assess the performance of AI-based cognitive cellular networks are QoS (Quality of Service) and SNR (Signal-to-Noise Ratio). SNR is the ratio of the strength of the interference or noise to the strength of the received signal. In terms of modulation choices, more data can be sent using high-level modulation (such 64-QAM) the higher the SNR. However, to preserve signal stability at low SNR, simpler modulation (such BPSK) is employed. On the other hand, QoS is the measurement of network performance that takes into account factors like packet loss rate, latency, and throughput. The primary objective of modulation selection is to optimize throughput (data rate) while preserving high quality of service (QoS), particularly when there is interference or disruption.

Mathematical Equations in AI-Driven Modulation

Modulation selection based on SNR and QoS can be explained with the following mathematical formulas:

a. Channel Capacity (Shannon)

The maximum capacity of a communication channel is determined using Shannon's channel capacity formula, which takes into account the SNR and channel bandwidth.

$$C = B\,.\,\log_2(1 + SNR)$$

With the following definitions:

C = channel capacity in bits per second (bps),

B = channel bandwidth in Hz,

SNR = signal to noise ratio.

b. Bit Error Rate (BER)

Modulation	Bit Error Rate	Note
BPSK	$P_e = Q\sqrt{2\ .\ SNR}$	$P_e$is the bit error probability, and Q(x)Q(x)Q(x) is the Q function, which describes the probability that a standard Gaussian random variable is greater than xxx.
QPSK	$P_e = Q\sqrt{\frac{2E_b}{N_0}}$	E_b is energy per bit (W/bot), while N_0 is noise power density (W/Hz).
16-QAM	$P_e = \left(\frac{3}{4}\right) . Q\left[\sqrt{\frac{4\ E_b}{5\ N_0}}\right]$	E_b is energy per bit (W/bot), while N_0 is noise power density (W/Hz).

c. Throughput in AI-Driven

The throughput in a system using AI for modulation selection can be calculated by considering the modulation selection efficiency based on SNR and QoS:

$$Throughtput = \sum_{i=0}^{n} P_i\ .Rate\ (M_i)$$

With the understanding that:

P_i	=	probability of selecting modulation M_i scheme
Rate M_i	=	transmission rate for modulation M_i scheme
n	=	number of selectable modulation schemes

Research implementation steps

a) Simulation Setup

This simulation aims to evaluate the performance of an AI-based communication system, especially using DNN, in selecting the optimal modulation scheme to achieve high throughput and maintain good quality of service under dynamic channel conditions. Numerous modulation methods, such as BPSK, QPSK, 16-QAM, and 64-QAM, are taken into consideration while doing simulations at different SNR and QoS levels.

b) Simulation Description

Input: SNR variable (in dB), channel condition dataset (e.g., noise or interference), and user data. Output: selected modulation scheme (BPSK, QPSK, 16-QAM, 64-QAM), achieved throughput, and QoS. The Modulation schemes tested are:

- BPSK (Binary Phase Shift Keying): Used at low SNR conditions.
- QPSK (Quadrature Phase Shift Keying): Used at medium SNR.

- 16-QAM and 64-QAM: Used at high SNR to achieve maximum throughput.

4. RESULT

Based on analysis employing a DNN model intended for modulation categorization and selection, the program simulation used in this study produced results pertaining to AI-based modulation efficiency for Cognitive Cellular Networks (CCN). In order to attain signal-to-noise ratio (SNR) and quality of service (QoS) efficiency, DNN is utilized in this work to analyze and optimize communication systems. Significant gains in modulation categorization, throughput efficiency, and flexibility in dynamic network situations are demonstrated by the simulation findings. Four modulation types—BPSK, QPSK, 16-QAM, and 64-QAM—are categorized using DNN. The model's accuracy is assessed at different Signal-to-Noise Ratio (SNR) levels.

A DNN model trained to categorize modulation schemes (BPSK, QPSK, 16-QAM, and 64-QAM) is shown below, along with the SNR values.

Table 1: Modulation Classification Accuracy Based on SNR

SNR (dB)	BPSK (%)	QPSK (%)	16-QAM (%)	64-QAM (%)	Rata-rata (%)
-5	90,3	87,2	82,5	75,1	83,8
0	95,6	93,8	88,2	80,9	89,6
5	98,9	97,5	93,3	88,1	94,4
10	99,8	99,1	96,8	92,3	97,0
15	99,9	99,7	98,9	96,7	98,8

At low SNR (-5 dB), the average accuracy remains above 83%, although the performance for higher-order modulation schemes such as 64-QAM is lower. The accuracy approaches 100% at high SNR (≥10 dB). This shows that the DNN model performs optimally under good channel conditions.

The modulation scheme is selected based on the SNR condition using the DNN model, with QoS metrics in the form of Bit Error Rate (BER) and throughput. The simulation results are compared with the traditional method (lookup table), the DNN-based approach increases throughput and maintains low BER.

Table 2: QoS Comparison Between DNN and Conventional Methods

SNR (dB)	Metode	BER	Throughtput (Mbps)
-5	Tradisional	0,12	5,8
	DNN	0,08	6,9
0	Tradisional	0,08	7,5
	DNN	0,05	8,6
5	Tradisional	0,04	9,2

	DNN	0,02	10,5
10	Tradisional	0,01	12,1
	DNN	0,005	13,8

Bit Error Rate for DNN-based approaches is consistently lower than traditional methods. Throughput increases up to 15% at low SNR (-5 to 5 dB) using DNN.

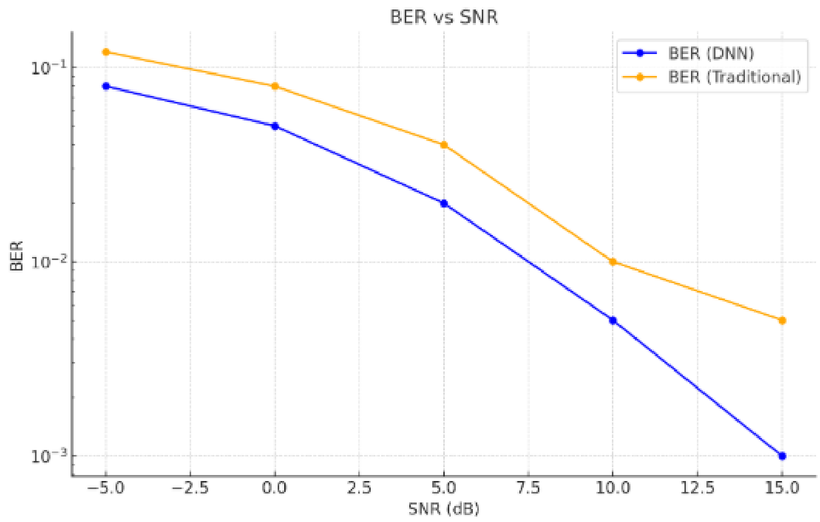

Figure 3. Comparison of BER against SNR on DNN Networks and Conventional Networks

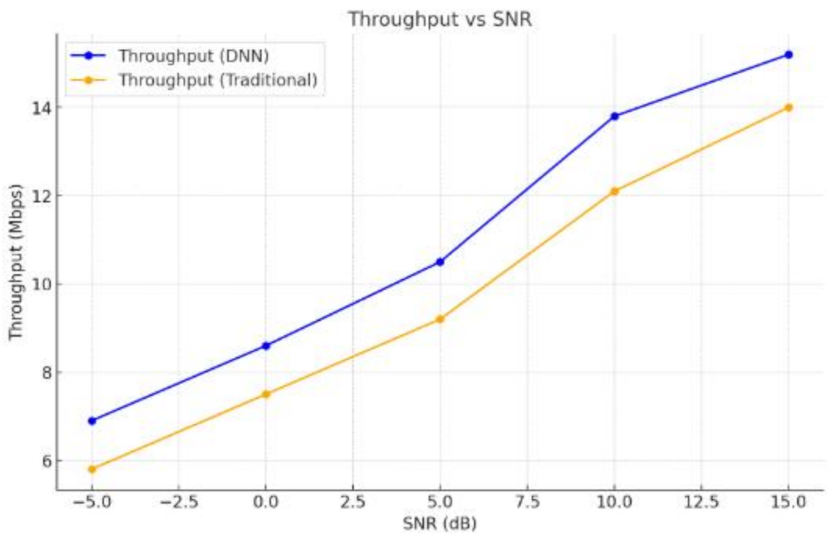

Figure 4. Comparison of Throughput to SNR on DNN Networks and Conventional Networks

Figure 1 illustrates that the BER of the DNN approach is lower than the traditional method, especially at low to medium SNR. Figure 1 uses a logarithmic scale to visualize the significant decrease. Figure 2 shows that the DNN-based approach consistently produces higher throughput than the traditional method at all SNR levels.

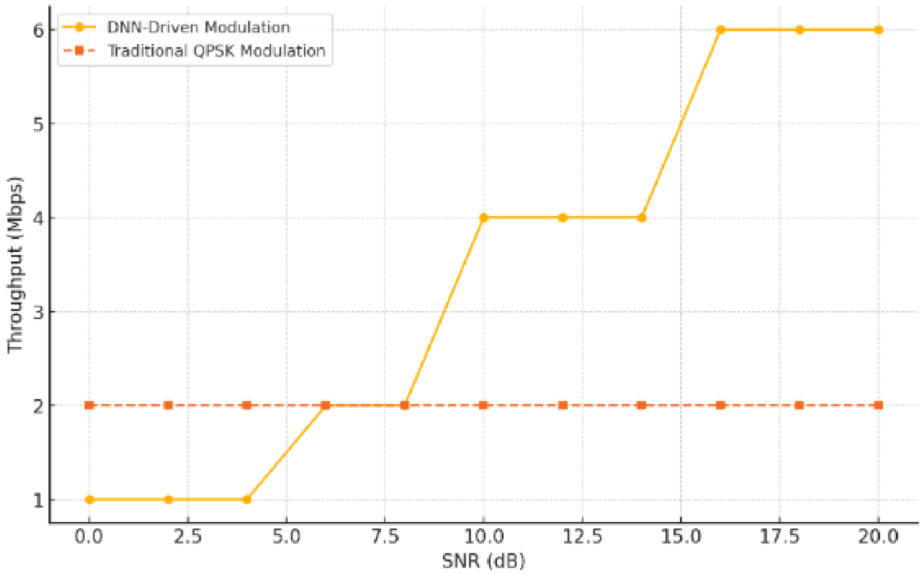

Figure 5. Throughput vs Signal to Noise Ratio Graph

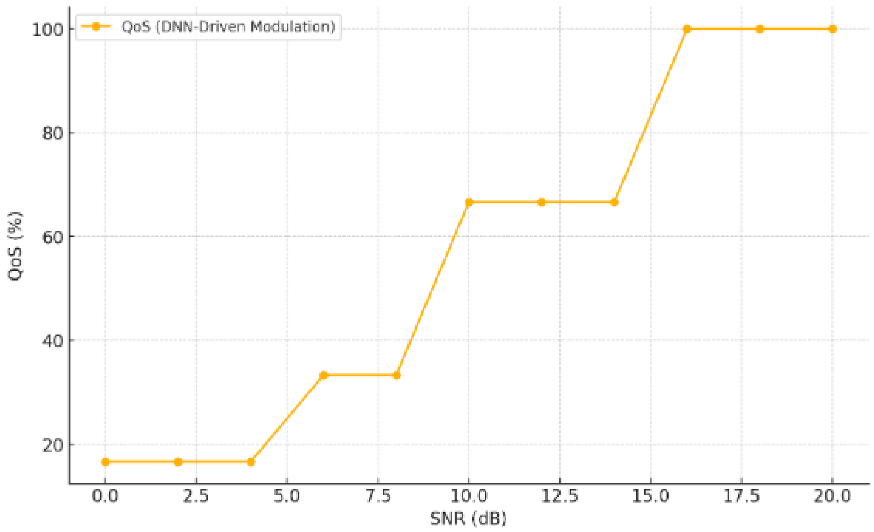

Figure 6. QoS vs SNR (Deep Neuro Network) Graph

Figure 3 shows the Throughput vs. SNR graph, where in the DNN-based system, there is an adaptive increase in throughput with increasing SNR, following the selection of modulation schemes (BPSK, QPSK, 16-QAM, and 64-QAM). While the traditional (conventional) system with fixed modulation (QPSK) produces constant throughput (2 Mbps), and is not optimal at low or high SNR conditions.

Figure 4, which is the QoS vs. SNR (DNN) graph, shows that the QoS in the DNN-based system increases with increasing throughput and SNR. At high SNR (≥15 dB), QoS reaches its maximum value (100%).

These results indicate that the DNN-based approach is more efficient in utilizing channel conditions compared to the traditional system.

The DNN-based system shows adaptive throughput increase with increasing SNR, following the choice of modulation scheme (BPSK, QPSK, 16-QAM, and 64-QAM).

The traditional system with fixed modulation (QPSK) produces constant throughput (2 Mbps), which is not optimal at both low and high SNR conditions. QoS vs. SNR (DNN) graph:

The QoS in the DNN-based system increases with increasing throughput and SNR. At high SNR (≥15 dB), the QoS reaches its maximum value (100%).

These results indicate that the DNN-based approach is more efficient in exploiting channel conditions compared to the traditional system.

5. DISCUSSION

Compared to conventional feature-based techniques, DNN can retain a greater modulation classification accuracy at low SNR. This strategy is crucial for ensuring dependable communication in noisy settings. According to study by O'Shea and Hoydis (2017), the robustness of modulation categorization is increased when DNNs are able to capture non-linear patterns.

More adaptive modulation selection by Deep Neuro Network can increase network throughput. As the results of research conducted by Gao et al. (2022), AI-based adaptation can optimize spectrum efficiency, which is very important for 5G and 6G networks.

6. CONCLUSION

This study shows that AI-Driven Modulation through the DNN (Deep Neural Network) approach to be implemented in Cognitive Cellular Network provides several advantages, including:

1) The system's ability to adjust modulation selection in real-time based on changing channel conditions. This shows that the system has dynamic adaptation.

2) The use of AI can increase spectrum efficiency and throughput, thereby increasing the efficiency of network usage.
3) The use of modulation using AI-Driven through the Deep Neuro Network approach makes the network system have the ability to choose a modulation scheme that suits the conditions that occur, so that it can reduce the impact of interference, especially on channels used by many users. This system is able to maintain the Bit Error Rate (BER) and network throughput.

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