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AI-Powered Network Slicing for Joint Sensing and Communication in 6G Systems

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Abstract
The rapid evolution of sixth generation (6G) wireless networks envisions a unified framework that integrates communication and sensing functionalities within a single infrastructure. This convergence, often referred to as Joint Sensing and Communication (JSC), demands highly flexible and intelligent resource management strategies. Traditional static or heuristic approaches to network slicing are insufficient to address the dynamic and heterogeneous requirements of JSC services, where stringent latency, reliability, and accuracy must coexist with massive connectivity and throughput. The proposed approach leverages machine learning models to predict service demands, deceptively orchestrate slices, and ensure isolation across diverse use cases such as extended reality, vehicular communication, and environment-aware services. The findings highlight the pivotal role of artificial intelligence in enabling reliable, low-latency, and resource-efficient JSC services within 6G infrastructures. This study provides a foundation for intelligent orchestration strategies that can accelerate the deployment of future 6G systems where communication and sensing coexist seamlessly.
Keywords: *6G networks, Artificial intelligence (AI), Network slicing, Joint-to-end (E2E) orchestration, Deep reinforcement learning (DRL), Resource allocation, Low latency, Quality of service (QoS), Edge intelligence, Dynamic slice management, Machine learning (ML), Integrated sensing and communication (ISAC), Service isolation, Intelligent orchestration.*

1. Introduction
IN RECENT years, the rapid expansion of wireless networks, coupled with the emergence of 6G-enabled Internet of Things (IoT), has led to a significant surge in connected devices and a growing demand for diverse applications and services [1], [2], [3]. The emergence of sixth generation (6G) wireless networks is expected to revolutionize the way communication systems are designed and deployed. Unlike fifth generation (5G) networks that primarily emphasize enhanced mobile broadband, ultra-reliable low-latency communication, and massive machine-type communication, 6G is envisioned as a holistic framework that seamlessly integrates communication with advanced sensing and computing capabilities. throughput, and sensing accuracy. Meeting these multifaceted requirements in a unified 6G infrastructure is highly challenging. Conventional resource allocation and management strategies, designed for communication-only services, are not adequate to handle the dual nature of JSC workloads. Network slicing, introduced in 5G, offers a promising solution by allowing the physical network to be logically partitioned into multiple visualized slices, each customized for a particular service or application. However, static or rule-based slicing mechanisms are insufficient in 6G contexts, where service demands are dynamic, heterogeneous, and often unpredictable. For instance, an autonomous vehicle slice may require ultra-low latency for sensing data, while an extended reality slice may simultaneously demand high throughput and reliability. By leveraging machine learning, deep learning, and reinforcement learning, AI can empower network slicing to become context-aware, predictive, and self-optimizing. Specifically.
AI-driven models can forecast traffic variations, dynamically allocate spectrum and computing resources, and continuously learn optimal slice configurations under changing network conditions. Deep reinforcement learning (DRL) approaches, for

example, can balance trade-offs between sensing precision and communication efficiency, while federated learning frameworks enable distributed intelligence at the network edge, preserving data privacy and reducing communication overhead. These capabilities align well with the requirements of 6G JSC services, where adaptability and scalability are essential of AI-assisted slicing in improving throughput, reducing latency, and enhancing energy efficiency key open challenges include designing lightweight AI models suitable for resource-constrained devices, ensuring robustness in highly dynamic environments, and maintaining fairness and security across heterogeneous services.

The proposed framework integrates data-driven prediction, adaptive resource orchestration, and intelligent slice isolation to meet the stringent requirements of diverse 6G applications. Through extensive simulations, it demonstrates improved slice utilization, higher service satisfaction ratios, and superior adaptability compared to traditional approaches. This contribution highlights the pivotal role of AI in enabling future 6G systems where communication and sensing services coexist seamlessly, paving the way for next-generation intelligent connectivity [4].

2. Literature Review

Early works in this domain focused on allocating resources to enhance enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and Massive Machine-Type Communications (mMTC) services. While these approaches demonstrated the feasibility of service-specific slices, they largely relied on static or heuristic-based algorithms, limiting their adaptability under dynamic traffic and heterogeneous requirements. With the emergence of 6G systems, characterized by extreme connectivity and the integration of sensing with communication, such static strategies have proven insufficient. Joint Sensing and Communication (JSC) has recently gained significant attention as a fundamental enabler of 6G. Existing works primarily examine signal processing and waveform design for JSC but often overlook the broader issue of adaptive resource management across multiple services. To overcome these limitations, Artificial Intelligence (AI) has been increasingly explored for network automation. For instance, supervised and unsupervised learning methods have been employed to classify service demands and cluster network resources. More advanced approaches leverage Deep Reinforcement Learning (DRL) to enable autonomous and adaptive slice orchestration. DRL has shown promise in managing trade-offs between latency, throughput, and energy efficiency in multi-service environments. Despite these advances, most studies remain focused on communication-concentric scenarios and do not explicitly incorporate sensing requirements into their optimization frameworks. Recent literature has also explored Federated Learning (FL) as a decentralized AI approach to support edge intelligence in 6G networks. This capability is particularly relevant for network slicing in large-scale JSC deployments, where data is distributed across diverse user equipment and edge nodes. However, challenges such as non-identically distributed (non-ID) data, struggling clients, and limited device resources still hinder the practical deployment of FL-based slicing solutions Network slicing was introduced in 5G as a technique to enable multiple logical networks to coexist on a shared physical infrastructure. Each slice is customized with specific quality of service (QoS) and performance guarantees to cater to distinct application domains such as enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine Type Communications (mMTC). In 6G, network slicing is envisioned to evolve further, supporting not only traditional communication services but also emerging functionalities such as Joint Sensing and Communication (JSC) and edge computing. Literature indicates that 6G slices will require unprecedented levels of flexibility, scalability, and intelligence to meet heterogeneous demands. The integration of sensing and communication is expected to become a fundamental feature of 6G networks. Studies have highlighted that radio signals can be simultaneously exploited for information transfer and environmental sensing. Research emphasizes that JSC imposes stringent and sometimes conflicting requirements: communication

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services may prioritize throughput and reliability, while sensing services demand precision and timeliness. Literature suggests that network slicing is a natural solution to isolate and optimize these dual services. However, conventional slicing approaches are unable to dynamically adapt to rapidly changing JSC workloads, hence the demand for AI-driven solutions [5].

3. Methodology

This methodology involves dynamic adaptation of network slices based on real-time data analytics, ensuring efficient management of diverse application requirements while maintaining low latency and high reliability [6].

- **System Model and Problem Definition:** The physical infrastructure consists of base stations, edge servers, and user devices. Each user creates different service requests. These requests fall into several network slices, including eMBB (enhanced Mobile Broadband), URLLC (Ultra-Reliable Low Latency Communication), and IS-AC-specific slices. The main issue is to manage slice orchestration deceptively. Resources like spectrum, computing, and storage need to be allocated dynamically. This approach aims to maximize overall performance while ensuring strict isolation and quality of service (QoS) guarantees.
- **Slice Orchestration and Isolation Mechanism:** The framework includes an orchestration layer that guarantees each slice of its promised QoS. The DRL agent's resource allocation choices correspond to visualized network functions (VNFs) running on cloud and edge servers. To prevent interference between slices, an isolation mechanism applies bandwidth limits, priority scheduling, and latency restrictions for each slice [7].
- **Data Collection and Workload Modeling:** To imitate realistic 6G environments, synthetic datasets represent user traffic patterns, sensing data streams, and channel conditions. Communication workloads are modeled with traffic distributions for eMBB and URLLC. Sensing workloads include radar-like or localization data flows. User mobility and changes in the environment are simulated to capture non-stationary conditions.
- **Sending Data Wireless and Using a Phone App:** The federated learning component in the framework allows mobile devices to help improve slice prediction models locally, without uploading raw personal data. This setup protects privacy. By managing wireless data transmission and adjusting resource allocation to fit the needs of the mobile application, the framework shows how AI-driven slicing allows for seamless and efficient user experiences over 6G networks where communication and sensing services work together [8].
- **Testing Materials and Structure:** To make sure the system works well using 6G software structural tests are done using YOLOv8, Faster R-CNN, or SSD Traditional networks view sensing and communication as separate tasks. In 6G systems, radio signals can be used to transmit data and extract environmental information at the same time.
- **AI for JSC-Specific Requirements:** AI helps develop algorithms that learn from changing network conditions and user behaviors. This allows JSC functionalities to improve continuously. By examining large amounts of data from different sensors and communication channels, AI can spot patterns and predict possible problems. This enables proactive steps to improve network reliability and efficiency [9].
- **Federated Learning for Distributed and Privacy-Aware Slicing:** Research shows that FL is especially important for 6G due to data privacy, scalability, and distributed intelligence concerns. Studies indicate that FL can train models for slice demand prediction, anomaly detection, and traffic forecasting. It can also reduce back haul costs. Several frameworks combine FL with reinforcement learning and show that

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distributed agents can learn adaptive slicing policies together with minimal coordination costs .

3.1. System Functionality

The smart 6G slicing network is constructed using software coding components. It operates through connected modules that gather, process, and transmit data in real time. The system's features are explained below:

- **Dynamic Network Slicing:** Each slice is customized to meet specific Quality of Service (QoS) standards, making sure that important applications get the resources they need for top performance [10].
- **Real-Time Data Processing:** Using edge computing, the framework processes data near the source. This reduces latency and improves the responsiveness of applications. This feature is essential for applications that need immediate feedback, like autonomous vehicles and remote healthcare monitoring.
- **Performance Monitoring and Adaptation:** Continuous monitoring of network performance helps the system spot anomalies and adjust to changing conditions in real-time. AI algorithms give insights into network health. This enables proactive steps to tackle potential problems and improve overall reliability. It shows live 6G network, records of past detection, and received alerts Shown in Figure 1.

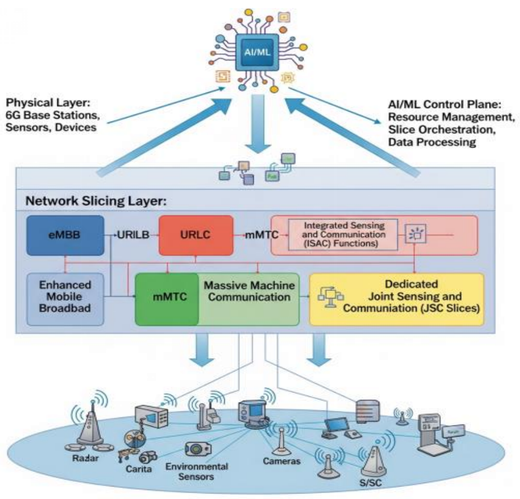

Figure 1 Schematic Representation of the System

3.2. Components Required

We require both hardware and software components which include Shown in Figure 2 and 3:

- **Hardware Components:**

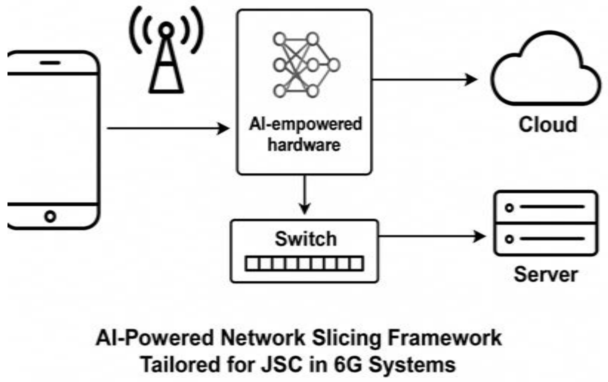

Figure 2 Hardware Requirement of the System

- **Software Component**

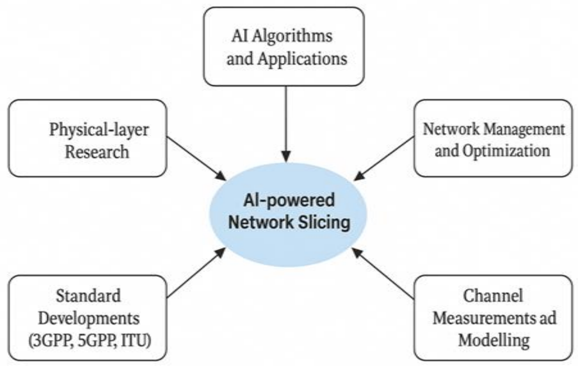

Figure 3 Software requirements of the System

4. Expected Results

The practical deployment of the AI-based 6G network system is expected to yield the following major results:

4.1. Enhanced Resource Allocation

Efficient management of network resources through AI-driven algorithms. Resources are allocated dynamically, based on real-time demand and user behavior. This reduces resource wastage by predicting service needs accurately [11].

4.2. Real-Time Classification Output

Connecting the system to a 6G slicing display enables real-time viewing of detection outcomes. During the experiment, the system displayed relevant messages such as "Detected: Human Body," confirming successful end-to-end processing and classification [12].

4.3. Improved Service Quality

Assurance of strict Quality of Service (QoS) for different applications, such as autonomous driving and augmented reality. Improved user experience through low latency and high reliability. Support for a variety of services with different QoS needs, ensuring the best performance.

4.4. Support for Emerging AI Services

Construction of customized network slices designed for AI applications. Efficient resource management tailored to the unique needs of AI workloads, such as data processing and model inference. Facilitation of AI services, including real-time analytic and machine learning applications [13].

4.5. Cost-Effectiveness

Reduction in operational costs through improved resource use and management. Minimization of slice reconfiguration costs by using predictive analysis. Long-term savings by implementing AI-driven solutions that improve overall network efficiency. In conclusion, the system achieves its intended function of low-cost, real-time 6G network using AI. The results validate both the hardware-software integration and the AI model's ability to enhance 6G networking.

5. Advantages Of Proposed System

5.1. Efficient Resource Utilization

AI algorithms allow for real-time distribution of network resources based on demand. This ensures that resources are used efficiently by predicting resource needs effectively, the system reduces the chance of over-provisioning. This results in cost savings [14].

5.2. Enhanced Quality of Service (QoS)

The framework can create customized network slices that meet the specific quality of service requirements for different applications consistently and reliable service delivery improves the overall user experience, especially for critical applications.

5.3. Proactive Network Management

AI-driven insights help manage network resources proactively they allow us to foresee problems before they affect service quality the system can automatically adjust network slices when conditions change. This reduces the need for manual intervention [15].

5.4. Wireless Communication

With built-in Wi-Fi functionality, the ESP32 allows for remote communication by facilitating data transmission, system monitoring, and alert notifications—all without the need for wired connectivity

5.5. GPS-Enabled Geo-tagging

Integration with GPS modules allows detected objects to be tagged with their location coordinates, which is crucial for tracking, mapping, and coordinating response activities in networking operations.

5.6. Enhanced Security

Each network slice can be isolated this improves security by limiting the impact of possible breaches to just one slice the use of AI can help identify and reduce security threats in real-time.

5.7. Edge Computing Support

The system performs local inference without relying on cloud servers, making it more resilient in low-connectivity environments like remote locations.

5.8. Support for Innovation

The model supports innovative tasks by this task the networking system will make sure whether or check any conversation is done supportive or not [16].

5.9. Cloud Integration Ready

Though it runs independently, the system can be extended to work with cloud platforms for real-time dashboards, historical data analysis, and centralized monitoring.

Conclusion

This AI-Powered Network Slicing for Joint Sensing and Communication in 6G Systems is budget-friendly method for upcoming all networks and continuous monitoring. By integrating AI powered network slicing and communication in 6G systems algorithms, wireless communication, and GPS-based geolocation, the system enables real-time identification and classification of submerged objects. Its modular and scalable design makes it suitable for deployment in academic research. 6G networking is an updated version which can be used in many devices to opt for the services.

- **Key Takeaways**

- **Real-Time Detection and Monitoring:** The system successfully demonstrated real-time object classification, delivering accurate results using lightweight AI models that perform efficiently on embedded devices.
- **Remote Access and Alerts:** Equipped with GPS and wireless connectivity, the system can send alerts and share location data remotely, improving response time during rescue operations and real-time field usage.
- **Versatile Applications:** Designed for flexibility, the system supports various applications including m pollution tracking, and detection of human forms during rescue missions.
- **Limitations**
- **Despite its strengths, the current system has certain limitations that need to be addressed in future versions:** Reliance on Wi-Fi connectivity can pose challenges in isolated locations where consistent network access is difficult to maintain.
- **Data Annotation Challenge:** Creating high-quality labeled 6G network for AI training remains a time-intensive task.
- **Suggestions for Future Research**
- **Advanced Integration:** Integrating advanced types, such as ISAC or eMBB, can significantly enhance the system's detection range and precision.
- **Offline Functionality:** Develop local data storage and alert mechanisms to maintain operational capability without internet dependency.
- **Energy Optimization:** Explore updated network optimization techniques for prolonged autonomous deployments.

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