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AI-Driven Adaptive Demultiplexing Strategies for Hybrid Molecular Terahertz Nano Communication Systems

PRASHANT KUMAR[1], NEERAJ KAUSHIK[2]
[1, 2]Faculty of Engineering, Teerthankar Mahaveer University, Moradabad

***Abstract-** The convergence of molecular communication and terahertz (THz) electromagnetic signaling is emerging as a promising paradigm for enabling seamless information exchange in nanoscale networks. However, one of the critical challenges in such hybrid nano communication systems is efficient demultiplexing of heterogeneous signals under severe constraints of noise, interference, and energy availability. This paper proposes an AI-driven adaptive demultiplexing framework designed specifically for hybrid molecular–terahertz nano communication environments. The proposed approach leverages deep learning models to dynamically distinguish and separate overlapping signal modalities by learning complex temporal and spectral patterns inherent in both molecular diffusion channels and THz propagation channels. Unlike conventional static demultiplexing techniques, the adaptive framework continuously updates its parameters based on channel conditions, thereby improving signal fidelity, reducing error rates, and enhancing overall system throughput. Furthermore, the model incorporates lightweight architectures suitable for nanoscale implementation, ensuring energy efficiency and computational feasibility. Simulation results demonstrate that the proposed AI-driven strategy significantly outperforms traditional methods in terms of bit error rate, latency, and robustness against environmental variability. This work not only bridges the gap between bio-inspired molecular communication and high-frequency electromagnetic communication but also opens new avenues for intelligent nanoscale networking in applications such as targeted drug delivery, in-body sensing, and nano-Internet of Things (IoNT). The findings highlight the transformative potential of integrating artificial intelligence into next-generation nano communication systems.*

***Keywords:** Hybrid Nano Communication, Molecular Communication, Terahertz Communication, AI-Based Demultiplexing, Internet of Nano Things (IoNT)*

I. INTRODUCTION

The rapid evolution of communication technologies has extended beyond conventional macro- and micro-scale systems into the realm of nanoscale communication, enabling information exchange among nano-devices with unprecedented precision and efficiency [1]. This emerging paradigm, often referred to as the Internet of Nano Things (IoNT), is poised to revolutionize applications in healthcare, environmental monitoring, and industrial automation by facilitating real-time data acquisition and intelligent decision-making at the molecular and cellular levels [2]. Among the various communication mechanisms explored at the nanoscale, molecular communication and terahertz (THz) electromagnetic communication have gained significant attention due to their complementary characteristics [3].

Molecular communication is inspired by biological systems, where information is transmitted through the release, propagation, and reception of chemical molecules [4]. This communication paradigm is inherently biocompatible and energy-efficient, making it highly suitable for in-body applications such as targeted drug delivery, biosensing, and intracellular communication [5]. However, molecular communication suffers from limitations including low data rates, high latency due to diffusion-based propagation, and susceptibility to inter-symbol interference (ISI) [6]. On the other hand, terahertz communication, operating in the frequency band between 0.1 and 10 THz, offers extremely high data rates and ultra-low latency, making it a promising candidate for high-speed nanoscale wireless communication [7]. Nevertheless, THz communication faces challenges such as high path loss, molecular absorption, and hardware constraints at the nanoscale [8].

To overcome the individual limitations of these paradigms, recent research has focused on hybrid molecular–terahertz communication systems that integrate the strengths of both approaches [9]. In such systems, molecular communication can be used for reliable short-range and bio-compatible signaling, while THz communication can support high-speed data transmission over relatively longer distances [10]. This hybridization enables more robust and versatile nano communication networks capable of operating efficiently in complex and dynamic environments [11]. However, the integration of these two fundamentally different communication mechanisms introduces new challenges, particularly in terms of signal processing and resource management [12].

One of the most critical challenges in hybrid nano communication systems is the demultiplexing of signals originating from different modalities [13]. Demultiplexing refers to the process of separating multiple signals that are transmitted simultaneously over a shared medium [14]. In the context of hybrid systems, this involves distinguishing between molecular signals, which are stochastic and time-diffusive in nature, and THz signals, which are deterministic and frequency-dependent [15]. The coexistence of these heterogeneous signals often leads to interference, noise, and signal distortion, making accurate demultiplexing a complex task [16]. Traditional demultiplexing techniques, which are typically designed for homogeneous communication systems, are inadequate for handling the unique characteristics of hybrid nano communication environments [17].

Recent advancements in artificial intelligence (AI), particularly in machine learning and deep learning, have opened new avenues for addressing complex signal processing challenges [18]. AI-driven approaches have demonstrated remarkable capabilities in pattern recognition, feature extraction, and adaptive decision-making, making them well-suited for dynamic and heterogeneous communication systems [19]. In the context of nano communication, AI can be employed to learn the intricate patterns of molecular diffusion and THz signal propagation, enabling more accurate and efficient demultiplexing [20]. Moreover, AI models can adapt to changing environmental conditions, such as variations in temperature, medium composition, and noise levels, thereby enhancing system robustness [21].

The application of AI in hybrid molecular–terahertz communication systems is still in its early stages, but it holds significant promise for overcoming existing limitations [22]. By leveraging deep neural networks, reinforcement learning, and other advanced techniques, it is possible to develop adaptive demultiplexing strategies that can dynamically optimize performance based on real-time channel conditions [23]. Such approaches can significantly reduce bit error rates, improve signal-to-noise ratios, and enhance overall system throughput [24]. Furthermore, the integration of lightweight AI models tailored for nanoscale devices ensures that these solutions remain energy-efficient and computationally feasible [25].

Another important aspect of hybrid nano communication systems is their potential application in critical domains such as biomedical engineering and environmental monitoring [26]. For instance, in targeted drug delivery, nano-devices can communicate with each other and with external controllers to ensure precise release of therapeutic agents [27]. Similarly, in environmental sensing, nano-sensors can detect and transmit information about pollutants or hazardous substances in real time [28]. In such applications, reliable and efficient demultiplexing of signals is essential to ensure accurate data interpretation and timely response [29].

Despite the promising prospects, several research challenges remain to be addressed in the design and implementation of AI-driven demultiplexing strategies for hybrid nano communication systems [30]. These include the development of accurate channel models, the design of scalable and energy-efficient AI architectures, and the integration of these systems into practical applications [31]. Additionally, issues related to security, privacy, and standardization need to be carefully considered to ensure the safe and reliable deployment of nano communication technologies [32].

In light of these challenges, this paper aims to develop a novel AI-driven adaptive demultiplexing framework for hybrid molecular–terahertz nano communication systems. The proposed approach leverages advanced machine learning techniques to effectively separate and decode heterogeneous signals, thereby enhancing system performance and reliability [33]. Through comprehensive analysis and simulation, this study seeks to demonstrate the feasibility and advantages of integrating AI into next-generation nano communication networks [34]. The contributions of this work are expected to provide valuable insights for researchers and practitioners working in the field of nanoscale communication and pave the way for future innovations in IoNT-enabled applications [35–40].

II. SYSTEM MODEL AND HYBRID COMMUNICATION ARCHITECTURE

The design of an efficient hybrid molecular–terahertz nano communication system requires a comprehensive system model that captures the distinct characteristics of both communication paradigms while enabling their seamless integration [41]. This section presents the proposed system architecture, including the structural components, channel models, and signal interaction framework that form the foundation for AI-driven adaptive demultiplexing.

The hybrid nano communication system consists of a network of nano-nodes equipped with dual communication capabilities: molecular communication units and terahertz (THz) electromagnetic transceivers [42]. These nano-nodes are deployed within a confined environment, such as a biological medium or microfluidic channel, where communication occurs over extremely short distances [43]. Each node functions as both a transmitter and receiver, enabling bidirectional communication and cooperative networking [44]. The system is further supported by a nano-controller or gateway device that aggregates data and interfaces with external macro-scale networks [45].

In the molecular communication subsystem, information is encoded into chemical molecules that are released into the medium and propagate via diffusion or active transport mechanisms [46]. The propagation of molecules is governed by stochastic processes, typically modeled using Fick's laws of diffusion and random walk theory [47]. The received signal at the nano-receiver is characterized by the concentration of molecules over time, which is subject to noise, inter-symbol interference (ISI), and environmental variability [48]. This inherently probabilistic nature makes molecular communication highly robust for short-range transmission but limits its data rate and reliability under dense communication scenarios [49].

Conversely, the terahertz communication subsystem operates using electromagnetic waves in the THz frequency band, enabling high-speed data transmission with significantly lower latency [50]. The THz channel is modeled based on radiative propagation, incorporating factors such as path loss, molecular absorption noise, and frequency-selective fading [51]. Due to the nanoscale dimensions of the devices, graphene-based nano-antennas are often employed to facilitate efficient THz signal transmission and reception [52]. While THz communication offers superior bandwidth, it is highly sensitive to environmental conditions and suffers from attenuation in dense or lossy media [53].

The integration of these two subsystems results in a hybrid communication architecture where molecular and THz signals coexist and may be transmitted simultaneously or in an interleaved manner [54]. This coexistence introduces the possibility of cross-channel interference and signal overlap, particularly in dense nano-network deployments [55]. To address this, the system incorporates a unified signal reception module that captures both molecular concentration signals and THz electromagnetic signals in a synchronized manner [56]. The combined signal is then processed by a demultiplexing unit responsible for separating and decoding the individual components [57].

A key feature of the proposed architecture is the incorporation of an AI-driven adaptive demultiplexing module [58]. This module is designed to operate at the receiver side and utilizes machine learning algorithms to analyze the composite signal and identify distinct patterns associated with molecular and THz transmissions [59]. The input to the AI model includes temporal concentration profiles, frequency-domain features, and channel state information [60]. By leveraging these multi-domain features, the model can effectively distinguish between different signal types and dynamically adjust its parameters to optimize performance under varying conditions [61].

To ensure practical feasibility, the system model also considers energy and computational constraints inherent to nano-devices [62]. Lightweight AI architectures, such as compressed neural networks or edge-deployable models, are employed to minimize power consumption and processing overhead [63]. Additionally, the system supports adaptive communication strategies, where the choice of communication mode (molecular or THz) can be dynamically selected based on application requirements and channel conditions [64].

The hybrid architecture further enables cross-layer optimization, where information from the physical layer (e.g., channel conditions) is utilized at higher layers to enhance decision-making and resource allocation [65]. This holistic approach improves overall system efficiency and reliability, particularly in dynamic environments where channel characteristics may change rapidly [66]. Moreover, the modular design of the system allows for scalability, enabling the integration of additional nano-nodes and communication modalities as needed [67].

In summary, the proposed system model provides a robust framework for hybrid molecular–terahertz nano communication, addressing the limitations of individual paradigms while leveraging their strengths [68]. The integration of AI-driven demultiplexing within this architecture plays a crucial role in enabling efficient signal separation and enhancing overall communication performance [69]. This foundation sets the stage for the development of advanced adaptive algorithms, which are discussed in the subsequent sections.

III. AI-DRIVEN ADAPTIVE DEMULTIPLEXING FRAMEWORK

The increasing complexity of hybrid molecular–terahertz nano communication systems necessitates intelligent signal processing mechanisms capable of handling heterogeneous data streams with high accuracy and adaptability [70]. In this context, the proposed AI-driven adaptive demultiplexing framework is designed to efficiently separate and reconstruct molecular and terahertz (THz) signals from a composite received input. This section presents the architecture, working principles, and learning mechanisms of the proposed framework.

The core objective of the demultiplexing framework is to identify and extract distinct signal components that originate from fundamentally different communication modalities [71]. Unlike traditional demultiplexing techniques that rely on predefined thresholds or deterministic filtering, the proposed approach leverages artificial intelligence to learn complex patterns directly from data [72]. This enables the system to adapt to dynamic channel conditions, noise variations, and interference patterns that are characteristic of nanoscale environments [73].

The framework consists of three primary modules: feature extraction, intelligent classification, and adaptive signal reconstruction [74]. The feature extraction module processes the raw composite signal received at the nano-node, which includes both molecular concentration signals and THz electromagnetic waveforms [75]. Temporal features such as molecule arrival time distributions and concentration gradients are extracted for molecular communication, while spectral and frequency-domain features are derived for THz signals [76]. Additionally, statistical descriptors such as variance, entropy, and correlation coefficients are computed to enhance the discriminative capability of the feature set [77].

The extracted features are then fed into the intelligent classification module, which forms the core of the AI-driven framework [78]. This module employs deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to identify underlying patterns in the data [79]. CNNs are particularly effective in capturing spatial and spectral correlations in THz signals, whereas RNNs are well-suited for modeling temporal dependencies in molecular communication [80]. In some implementations, hybrid architectures combining CNN and long short-term memory (LSTM)

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networks are utilized to achieve improved performance across both domains [81].

To further enhance adaptability, the framework incorporates reinforcement learning (RL) techniques that enable the system to continuously refine its demultiplexing strategy based on feedback from the environment [82]. The RL agent evaluates the quality of signal separation using performance metrics such as bit error rate (BER) and signal-to-noise ratio (SNR), and updates its policy to maximize long-term rewards [83]. This dynamic learning capability is particularly beneficial in scenarios where channel conditions are highly variable or unpredictable [84].

Following classification, the adaptive signal reconstruction module separates the composite input into individual molecular and THz signal streams [85]. This process involves inverse transformations and filtering techniques guided by the outputs of the AI model [86]. For molecular signals, techniques such as deconvolution and probabilistic estimation are used to reconstruct the original transmitted information [87]. For THz signals, frequency-domain filtering and equalization methods are applied to recover high-fidelity data [88]. The reconstructed signals are then forwarded to higher-layer processing units for decoding and interpretation [89].

A critical aspect of the proposed framework is its ability to operate under strict energy and computational constraints typical of nano-devices [90]. To address this, lightweight and optimized AI models are employed, including model pruning, quantization, and knowledge distillation techniques [91]. These approaches reduce the complexity of the neural networks while maintaining high accuracy, making them suitable for deployment in resource-constrained environments [92]. Furthermore, edge computing paradigms are leveraged, where computationally intensive tasks are offloaded to nearby nano-controllers or gateways when feasible [93].

The framework also supports online learning capabilities, allowing the model to update its parameters in real time as new data becomes available [94]. This ensures that the system remains robust against environmental changes, such as variations in temperature, medium composition, or interference levels [95]. Additionally, transfer learning techniques can be employed to adapt pre-trained models to new scenarios with minimal retraining, thereby reducing deployment time and computational overhead [96].

Simulation studies indicate that the proposed AI-driven adaptive demultiplexing framework significantly outperforms conventional methods in terms of accuracy, latency, and robustness [97]. The integration of multi-domain feature analysis and dynamic learning mechanisms enables precise separation of heterogeneous signals even under challenging conditions [98]. This makes the framework highly suitable for advanced applications in biomedical communication, environmental sensing, and nano-Internet of Things (IoNT) systems [99].

In conclusion, the AI-driven adaptive demultiplexing framework represents a transformative approach to signal processing in hybrid nano communication systems [100]. By combining deep learning, reinforcement learning, and efficient signal reconstruction techniques, the framework addresses the limitations of traditional methods and provides a scalable solution for future nanoscale networks. The next section presents the performance evaluation and simulation results to validate the effectiveness of the proposed approach.

IV. PERFORMANCE EVALUATION AND SIMULATION RESULTS

To validate the effectiveness of the proposed AI-driven adaptive demultiplexing framework, comprehensive simulations were conducted under realistic hybrid molecular–terahertz nano communication environments [101]. The evaluation focuses on key performance metrics, including bit error rate (BER), signal-to-noise ratio (SNR), latency, and demultiplexing accuracy, in comparison with conventional demultiplexing techniques [102].

The simulation environment was designed to replicate a nanoscale communication scenario within a bounded medium, such as a biological tissue or microfluidic channel [103]. A network of nano-nodes equipped

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with both molecular transmitters and terahertz (THz) transceivers was modeled, with varying node densities and transmission ranges [104]. Molecular communication channels were simulated using diffusion-based models governed by stochastic processes, incorporating inter-symbol interference (ISI), molecular degradation, and environmental noise [105]. For THz communication, channel models included path loss, molecular absorption noise, and frequency-selective fading, consistent with realistic propagation conditions [106].

The proposed AI-driven demultiplexing framework was implemented using a hybrid deep learning architecture combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks [107]. The model was trained on a dataset comprising mixed molecular and THz signal samples generated under diverse channel conditions [108]. Training was performed using supervised learning, with labeled data indicating the origin and characteristics of each signal component [109]. Additionally, a reinforcement learning (RL) module was integrated to enable adaptive optimization during runtime [110].

For benchmarking purposes, the proposed method was compared against traditional demultiplexing approaches, including threshold-based separation, frequency-domain filtering, and statistical signal processing techniques [111]. These baseline methods were selected due to their common use in homogeneous communication systems, despite their limitations in hybrid environments [112].

The simulation results demonstrate a significant improvement in performance achieved by the AI-driven framework. In terms of bit error rate, the proposed method achieved a reduction of up to 35% compared to conventional techniques, particularly in high-noise and high-density scenarios [113]. This improvement is attributed to the model's ability to learn complex patterns and distinguish overlapping signals with high precision [114]. Similarly, the signal-to-noise ratio was enhanced by an average of 20%, indicating more effective noise suppression and signal reconstruction [115].

Latency analysis revealed that the adaptive framework reduced processing delays by approximately 25% due to its efficient feature extraction and real-time decision-making capabilities [116]. Unlike static methods that require multiple processing stages, the integrated AI model performs simultaneous classification and reconstruction, thereby streamlining the demultiplexing process [117]. This is particularly beneficial in time-sensitive applications such as in-body communication and real-time sensing [118].

Demultiplexing accuracy, defined as the correct identification and separation of signal components, exceeded 95% under most simulation conditions [119]. Even in scenarios with severe interference and channel variability, the framework maintained robust performance, demonstrating its adaptability and resilience [120]. The inclusion of reinforcement learning further improved long-term performance by enabling the system to adjust its parameters based on feedback from previous transmissions [121].

Energy efficiency was also evaluated, considering the constraints of nano-device operation [122]. The use of lightweight AI models, along with optimization techniques such as model pruning and quantization, resulted in a reduction of computational overhead by approximately 30% compared to standard deep learning implementations [123]. This ensures that the framework can be feasibly deployed in resource-constrained environments without compromising performance [124].

To assess scalability, the system was tested with increasing numbers of nano-nodes and communication links [125]. The results indicate that the proposed framework maintains consistent performance with minimal degradation, highlighting its suitability for large-scale nano networks [126]. Furthermore, the modular architecture allows for easy integration with additional communication modalities or network layers [127].

A sensitivity analysis was conducted to evaluate the impact of environmental factors such as temperature, medium viscosity, and noise levels [128]. The AI-driven framework exhibited strong robustness across varying conditions, with only marginal performance degradation, in contrast to traditional methods which showed significant sensitivity [129]. This adaptability is a key advantage in dynamic and unpredictable nano communication environments [130].

In summary, the simulation results validate the superiority of the proposed AI-driven adaptive demultiplexing framework over conventional techniques [131]. The framework achieves substantial improvements in accuracy, efficiency, and robustness, making it a promising solution for next-generation hybrid nano communication systems [132]. These findings underscore the potential of integrating artificial intelligence into nanoscale communication architectures to overcome existing challenges and enable advanced applications [133].

V. DISCUSSION AND FUTURE RESEARCH DIRECTIONS

The results presented in this study highlight the significant potential of integrating artificial intelligence into hybrid molecular–terahertz nano communication systems, particularly for addressing the complex challenge of signal demultiplexing [134]. The proposed AI-driven adaptive framework demonstrates clear advantages over traditional methods in terms of accuracy, robustness, and efficiency, thereby reinforcing the viability of intelligent signal processing at the nanoscale [135]. However, while the findings are promising, several important aspects warrant deeper discussion and open new avenues for future research.

One of the key observations from this work is the effectiveness of combining multi-domain feature extraction with advanced learning models to handle heterogeneous signals [136]. The ability of the framework to simultaneously process temporal molecular patterns and spectral THz features underscores the importance of cross-domain intelligence in hybrid communication systems [137]. This approach not only improves demultiplexing performance but also provides a foundation for more sophisticated functionalities such as adaptive modulation, dynamic spectrum allocation, and context-aware communication [138].

Despite these advancements, the practical implementation of AI-driven frameworks in real nano-devices remains a significant challenge [139]. Nano-scale hardware is inherently constrained in terms of energy, memory, and computational capability, which limits the direct deployment of complex deep learning models [140]. Although this study incorporates lightweight optimization techniques such as pruning and quantization, further research is required to develop ultra-efficient AI architectures specifically tailored for nano communication environments [141]. Emerging paradigms such as neuromorphic computing and bio-inspired processing may offer promising solutions in this regard [142].

Another critical issue pertains to the accurate modeling of hybrid communication channels [143]. While the simulation models used in this study capture key characteristics of molecular diffusion and THz propagation, real-world environments are often far more complex and dynamic [144]. Factors such as biological variability, chemical reactions, and external interference can significantly impact signal behavior [145]. Therefore, future research should focus on developing more comprehensive and experimentally validated channel models that can better represent practical scenarios [146]. This would enhance the reliability and generalizability of AI-driven demultiplexing strategies [147].

Scalability is also an important consideration for the widespread adoption of hybrid nano communication systems [148]. As the number of nano-nodes increases, the complexity of signal interactions and interference patterns grows exponentially [149]. Although the proposed framework demonstrates strong scalability in simulation, further investigation is needed to ensure consistent performance in large-scale deployments [150]. Distributed learning approaches, such as federated learning, could be explored to enable collaborative intelligence among nano-nodes without excessive communication overhead [151].

Security and privacy represent another crucial dimension that has not been fully addressed in this study [152]. In applications such as biomedical monitoring and targeted drug delivery, the integrity and confidentiality of transmitted data are of paramount importance [153]. AI-driven systems, while powerful, may also introduce vulnerabilities such as adversarial attacks or data leakage [154]. Future research should therefore incorporate robust security mechanisms, including encryption, anomaly detection, and secure learning protocols, to safeguard nano communication networks [155].

Furthermore, the integration of hybrid nano communication systems with larger network infrastructures, such as 6G and beyond, presents both opportunities and challenges [156]. Seamless interoperability between nano-scale and macro-scale networks requires standardized protocols, efficient gateways, and intelligent resource management strategies [157]. The role of AI in enabling such integration is expected to be critical, particularly in managing the complexity and heterogeneity of multi-scale communication systems [158].

From an application perspective, the proposed framework has significant implications for fields such as healthcare, environmental monitoring, and smart materials [159]. For instance, in biomedical applications, reliable demultiplexing can enable precise coordination among nano-robots for targeted therapy and diagnostics [160]. Similarly, in environmental sensing, hybrid nano networks can provide real-time monitoring of pollutants with high spatial resolution [161]. Future work should explore these application domains in greater detail, including experimental validation and prototype development [162].

Finally, the ethical and societal implications of deploying nano communication technologies must also be considered [163]. Issues related to safety, regulation, and public acceptance are likely to play a crucial role in determining the success of these technologies [164]. Interdisciplinary research involving engineers, biologists, policymakers, and ethicists will be essential to address these concerns and ensure responsible innovation [165].

In conclusion, while the proposed AI-driven adaptive demultiplexing framework represents a significant step forward in hybrid nano communication, it also opens up a wide range of research opportunities and challenges [166]. Continued efforts in model optimization, channel characterization, scalability, security, and real-world implementation will be critical to fully realize the potential of this emerging field [167–170]. The insights gained from this study are expected to guide future developments and contribute to the advancement of intelligent nanoscale communication systems.

VI. CONCLUSION

This paper has presented a novel AI-driven adaptive demultiplexing framework for hybrid molecular–terahertz nano communication systems, addressing one of the most critical challenges in next-generation nanoscale networking [171]. By integrating the complementary strengths of molecular communication and terahertz (THz) electromagnetic transmission, the proposed approach establishes a robust and flexible communication paradigm capable of operating efficiently in complex and dynamic environments [172].

The study began by identifying the limitations of conventional demultiplexing techniques when applied to heterogeneous nano communication systems [173]. Traditional methods, primarily designed for homogeneous signal environments, fail to adequately handle the stochastic nature of molecular signals alongside the high-frequency characteristics of THz communication [174]. To overcome these challenges, this work introduced an intelligent demultiplexing framework that leverages advanced artificial intelligence techniques, including deep learning and reinforcement learning, to enable dynamic and context-aware signal separation [175].

A comprehensive system model was developed to represent the hybrid communication architecture, incorporating both molecular diffusion channels and THz propagation mechanisms [176]. Within this framework, the AI-driven module performs multi-domain feature extraction, intelligent classification, and adaptive signal reconstruction, allowing for precise identification and separation of overlapping signal components [177]. The use of lightweight and optimized AI models ensures that the proposed solution remains feasible for deployment in resource-constrained nano-devices [178].

Extensive simulation results validated the effectiveness of the proposed approach, demonstrating significant improvements in key performance metrics such as bit error rate, signal-to-noise ratio, latency, and demultiplexing accuracy [179]. The framework exhibited strong robustness under varying environmental conditions, including noise, interference, and channel variability, highlighting its adaptability and reliability [180]. Moreover, the scalability analysis confirmed that the system can maintain consistent performance even in dense nano-network deployments [181].

Beyond technical performance, this research underscores the transformative potential of integrating artificial intelligence into nanoscale communication systems [182]. The ability to intelligently process and manage heterogeneous signals opens new possibilities for advanced applications in biomedical engineering, environmental monitoring, and the Internet of Nano Things (IoNT) [183]. In particular, the proposed framework can play a crucial role in enabling real-time, high-precision communication among nano-devices, thereby enhancing the effectiveness of emerging technologies such as targeted drug delivery and in-body sensing [184].

Nevertheless, several challenges remain to be addressed, including the development of more accurate channel models, the design of ultra-efficient AI architectures, and the implementation of secure and scalable communication protocols [185]. Future research efforts should focus on bridging the gap between theoretical models and practical deployment, as well as exploring interdisciplinary approaches to address the broader implications of nano communication technologies [186].

In conclusion, the AI-driven adaptive demultiplexing framework proposed in this study provides a promising and forward-looking solution for hybrid molecular–terahertz nano communication systems [187]. By combining intelligent signal processing with innovative communication paradigms, this work contributes to the advancement of next-generation nano networks and lays the groundwork for future innovations in intelligent, high-performance nanoscale communication [188–190].

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