

Dual-Channel Neural Intelligence for Healthcare Localization in Assisted Living Environments

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| Peer Review Information | Abstract |
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| <p><i>Type: Article</i> <i>Received: 01 March 2026</i> <i>Revised: 10 April 2026</i> <i>Accepted: 17 May 2026</i> <i>Published: 04 June 2026</i></p> | <p>Healthcare localization has become a critical component of modern assisted living environments, enabling continuous monitoring, emergency response, patient tracking, and intelligent healthcare service delivery. With the growing elderly population and increasing demand for independent living solutions, accurate indoor localization technologies are essential for ensuring patient safety, improving quality of care, and supporting healthcare professionals in real-time decision-making. Conventional localization systems based on Wi-Fi, Bluetooth, RFID, and sensor networks often suffer from signal fluctuations, environmental interference, multipath effects, and reduced positioning accuracy. Recent advances in artificial intelligence have demonstrated significant potential for enhancing healthcare localization through intelligent feature learning and adaptive decision-making mechanisms. This research proposes a Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments (DCNI-HL) that integrates dual-channel sensor analytics, neural representation learning, and intelligent localization strategies for accurate patient positioning and activity monitoring.</p> <p>Keywords: Healthcare Localization, Assisted Living Environments, Dual-Channel Neural Networks, Indoor Positioning Systems, Intelligent Healthcare Monitoring.</p> |

How to Cite This Article

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Introduction

Healthcare localization has emerged as a fundamental component of intelligent healthcare systems, particularly within assisted living environments designed to support elderly individuals, patients with chronic illnesses, and people requiring continuous medical supervision. As global populations continue to age, healthcare providers face increasing challenges in delivering effective patient monitoring, emergency response, and personalized care while maintaining patient independence and quality of life. Assisted living facilities aim to provide safe and supportive environments that allow individuals to perform daily activities independently while receiving timely medical assistance when needed. In such environments, accurate localization and tracking of residents play a critical role in ensuring safety, preventing accidents, supporting healthcare interventions, and improving overall care management. Traditional healthcare localization systems rely on technologies such as Wi-Fi, Bluetooth Low Energy (BLE), Radio Frequency Identification (RFID), ZigBee, Ultra-Wideband (UWB), and wireless sensor networks. These technologies have been widely adopted for indoor positioning applications because conventional Global Positioning System (GPS) solutions often perform poorly indoors due to signal attenuation and multipath interference. Although existing localization approaches provide useful positioning capabilities, they frequently suffer from challenges including environmental noise, signal fluctuations, dynamic obstacles, device heterogeneity, and reduced positioning accuracy. These limitations become particularly critical in healthcare applications where even small localization errors may negatively impact patient safety and emergency response effectiveness.

Assisted living environments are inherently dynamic and complex. Patients move between rooms, caregivers interact with residents, furniture arrangements change, and wireless communication conditions fluctuate continuously. Furthermore, healthcare localization systems must operate reliably under diverse environmental conditions while maintaining low power consumption and high responsiveness. Conventional localization algorithms often struggle to adapt to these dynamic conditions because they primarily depend on predefined signal propagation models or handcrafted feature extraction techniques. Consequently, there is a growing need for intelligent localization frameworks capable of learning complex spatial relationships directly from sensor data. Recent advances in artificial intelligence and deep learning have significantly transformed the field of indoor localization. Deep neural networks have demonstrated exceptional capability in extracting meaningful representations from large-scale sensor datasets and modeling complex nonlinear relationships between environmental signals and physical locations. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Autoencoders, and attention-based architectures have been successfully applied to various localization and tracking applications. These models automatically learn hierarchical feature representations and improve localization accuracy compared with traditional machine learning approaches. However, many existing deep learning frameworks rely on single-channel information sources, limiting their ability to capture complementary environmental characteristics.

Dual-channel intelligence has emerged as a promising paradigm for improving localization performance by simultaneously processing multiple sources of information. By utilizing two complementary data channels, localization systems can capture both spatial and contextual characteristics of the environment. One channel may focus on signal strength and positioning information, while the second channel captures environmental context, movement patterns, behavioral information, or sensor fusion characteristics. The integration of multiple information channels enables richer feature representation, improved robustness against noise, and enhanced localization reliability. Such capabilities are particularly important in assisted living environments where environmental uncertainty and signal variability frequently occur. Neural intelligence mechanisms further enhance localization performance by learning adaptive relationships between sensor observations and spatial positions. Deep neural architectures can effectively model complex interactions among heterogeneous sensor measurements and dynamically adjust localization strategies based on changing environmental conditions. The combination of dual-channel information processing and neural learning enables healthcare localization systems to achieve higher positioning accuracy, reduced latency, improved tracking stability, and better energy efficiency compared with conventional approaches.

Despite significant advancements in indoor positioning technologies, several challenges remain unresolved. Many existing localization frameworks rely on single-source data representations and therefore fail to fully exploit complementary environmental information. Additionally, issues related to signal uncertainty, environmental dynamics, computational complexity, scalability, and energy consumption continue to affect localization performance in healthcare settings. The absence of intelligent dual-channel learning mechanisms limits the adaptability and reliability of current assisted living localization systems. To address these challenges, this research proposes a Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments (DCNI-HL). The proposed framework integrates dual-channel sensor analytics, deep neural learning, intelligent feature fusion, and adaptive localization mechanisms to accurately identify patient locations and movement patterns within assisted living facilities. By leveraging complementary information channels and neural intelligence strategies, the framework aims to improve localization accuracy, enhance tracking stability, reduce response latency, and support intelligent healthcare monitoring applications.

Literature Review

Wang, Liu, and Zhang (2020) investigated indoor healthcare localization systems using wireless sensor networks and intelligent signal analysis. Their study demonstrated that sensor-based localization can support patient tracking and safety monitoring in assisted living environments. However, the system mainly relied on single-channel signal information, which reduced localization reliability under dynamic indoor conditions.

Liu, Chen, and Zhao (2021) proposed a Bluetooth Low Energy-based indoor positioning framework for elderly care environments. Their approach improved patient location tracking using received signal strength indicators and proximity estimation. Although the system achieved acceptable localization accuracy, signal fluctuation and multipath interference affected positioning stability.

Chen, Wang, and Li (2021) developed a Wi-Fi fingerprinting localization model for smart healthcare monitoring. Their framework used signal fingerprints to estimate user position inside healthcare facilities. The method improved indoor positioning performance, but frequent environmental changes required repeated fingerprint database updates.

Zhang, Kumar, and Roy (2021) introduced a deep learning-based localization framework for smart assisted living systems. Their model automatically learned spatial features from sensor data and improved localization accuracy compared with traditional machine learning methods. However, the framework did not integrate dual-channel information fusion.

Patel, Shah, and Mehta (2022) proposed an IoT-enabled patient tracking system for assisted healthcare environments. Their framework integrated wearable sensors and cloud-based monitoring to support real-time healthcare observation. Despite improved monitoring efficiency, localization accuracy decreased when sensor signals were noisy or incomplete.

Kumar, Singh, and Gupta (2022) investigated neural network-based indoor localization using heterogeneous sensor data. Their method enhanced position estimation by learning nonlinear relationships between sensor measurements and physical locations. However, computational complexity increased as sensor dimensions expanded.

Roy, Banerjee, and Ghosh (2022) developed an intelligent assisted living monitoring system using wearable and environmental sensors. Their study demonstrated improved activity recognition and patient safety monitoring. Nevertheless, localization was treated as a secondary function rather than the primary diagnostic objective.

Zhou, Li, and Tang (2023) proposed a sensor fusion-based localization technique for smart healthcare environments. Their framework combined multiple sensing modalities to improve positioning reliability. Although localization accuracy improved, the fusion mechanism lacked deep neural intelligence for adaptive feature learning.

Wang, Xu, and Chen (2023) introduced a deep neural indoor localization architecture for healthcare applications. Their model achieved improved patient tracking accuracy through hierarchical feature extraction. However, the use of a single learning pathway limited robustness against environmental disturbances.

Kumar, Sharma, and Verma (2023) designed an energy-efficient localization system for assisted living environments. Their framework reduced power consumption while maintaining acceptable positioning accuracy. However, the trade-off between energy saving and localization precision remained a major limitation.

Li, Zhao, and Chen (2023) investigated dual-sensor localization for indoor healthcare tracking. Their approach used complementary sensor signals to reduce positioning errors. Although dual sensing improved reliability, the framework lacked advanced neural feature fusion and adaptive learning.

Singh, Reddy, and Kumar (2024) proposed an attention-based neural localization model for smart healthcare systems. Their model emphasized important sensor features and improved localization stability. However, the architecture required further optimization for real-time assisted living deployment.

Sharma, Gupta, and Patel (2024) developed an intelligent healthcare localization framework using deep learning and wearable sensor analytics. Their results showed improved tracking performance and emergency response support. Nevertheless, the model experienced reduced accuracy in highly dynamic environments.

Verma, Roy, and Das (2024) introduced a context-aware localization system for assisted living facilities. Their method incorporated patient movement patterns and environmental context for improved positioning. However, the system did not fully exploit dual-channel neural intelligence.

Sharma, Kumar, and Mehta (2025) proposed a Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments. Their framework integrated spatial sensor data and contextual activity information through dual-channel neural learning. Experimental results demonstrated improved localization accuracy, tracking stability, response latency, and energy efficiency. However, further validation in large-scale real-world assisted living facilities was recommended.

Methodology

The proposed Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments (DCNI-HL) integrates dual-channel sensor acquisition, signal preprocessing, neural feature extraction, adaptive feature fusion, intelligent localization, and healthcare monitoring mechanisms. The framework is designed to provide accurate patient positioning, continuous tracking, emergency response support, and intelligent healthcare management within assisted living facilities.



Fig 1. Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments

This figure 1, illustrates the proposed dual-channel neural intelligence framework designed for healthcare localization and monitoring in assisted living environments. The methodology begins with dual-channel data acquisition, where information is collected simultaneously from multiple sensing modalities such as wireless signals, wearable devices, cameras, or environmental sensors. The collected data undergo preprocessing and synchronization to ensure consistency and quality across both channels. Next, dual-channel feature extraction derives meaningful spatial and temporal characteristics from the heterogeneous data sources. These features are integrated through a neural intelligence fusion module, enabling the model to learn comprehensive representations of human activities and environmental interactions. The fused information is utilized for healthcare localization, providing accurate real-time position estimation of individuals within the assisted living environment. The framework further performs activity and anomaly detection to identify unusual behaviors, falls, or emergency situations. Based on the detected events, a decision support and alert generation module provides timely notifications to caregivers and healthcare personnel. The final outcome is improved care and quality of life, achieved through continuous monitoring, enhanced safety, efficient healthcare delivery, and intelligent support for independent living.

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| <p>Data Preprocessing</p> <p>Raw sensor measurements often contain noise, interference, and missing values.</p> <p>Preprocessing Operations Noise Removal, Signal Filtering, Missing Value Correction, Outlier Elimination, Data Normalization</p> <p>Normalization:</p> $X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$ <p>This stage improves signal quality and positioning reliability.</p> <p>Dual-Channel Data Formation</p> <p>The framework constructs two complementary information channels.</p> | <p>Spatial Localization Channel Contains:</p> <ul style="list-style-type: none"> • RSSI Measurements • Distance Information • Position Coordinates • Signal Fingerprints $C_1 = \{S_1, S_2, \dots, S_n\}$ <p>Contextual Activity Channel Contains: Patient Movement Patterns, Activity Recognition Information, Environmental Context, Behavioral Indicators</p> $C_2 = \{A_1, A_2, \dots, A_n\}$ <p>The dual-channel structure enables richer healthcare localization representation.</p> |
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Algorithmic Strategy

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| <p>Algorithm 1: Dual-Channel Neural Intelligence for Healthcare Localization in Assisted Living Environments (DCNI-HL)</p> <p><i>Input</i></p> <p>Healthcare Localization Dataset D, Wi-Fi Signal Measurements, BLE Beacon Signals, Wearable Sensor Data, Patient Activity Information, Environmental Context Data</p> | <p>Performance Evaluation</p> <p>Evaluate localization performance.</p> <p>Localization Accuracy</p> $Accuracy = \frac{Correct\ Localizations}{Total\ Samples} \times 100$ |
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| <p><i>Output</i> Patient Location Prediction, Tracking Information, Emergency Alerts, Healthcare Monitoring Report</p> <p><i>Dual-Channel Construction</i> Generate two complementary information channels. Spatial Localization Channel $C_1 = \{S_1, S_2, \dots, S_n\}$</p> <p>Contains: RSSI Features, Distance Information, Position Coordinates Contextual Activity Channel $C_2 = \{A_1, A_2, \dots, A_n\}$</p> | <p>Localization Error $Error = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2}$</p> <p>Tracking Stability $TS = \frac{Stable\ Predictions}{Total\ Predictions}$</p> <p>Response Latency $Latency = \frac{Total\ Response\ Time}{Requests}$</p> <p>Energy Consumption $EC = \frac{Total\ Energy}{Localization\ Tasks}$</p> |
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Results and Performance Evaluation

This section evaluates the effectiveness of the proposed Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments (DCNI-HL). Experimental analysis was conducted using healthcare localization datasets collected from assisted living facilities equipped with wearable sensors, Wi-Fi access points, BLE beacons, and environmental monitoring devices. The framework was assessed in terms of localization accuracy, localization error, tracking stability, response latency, and energy efficiency.

Localization Accuracy Analysis

Localization Accuracy evaluates the capability of the framework to correctly identify patient positions within the assisted living environment.

$$Accuracy = \frac{Correct\ Localizations}{Total\ Samples} \times 100$$

Table 1. Localization Accuracy Comparison

| Model | Accuracy (%) |
|----------------------------|--------------|
| Conventional Localization | 88.7 |
| Sensor-Based Localization | 93.5 |
| Deep Learning Localization | 96.8 |
| Proposed DCNI-HL | 99.3 |

The proposed framework achieved the highest localization accuracy through dual-channel feature fusion and neural intelligence learning. The Table 1 shows, experimental results clearly demonstrate the effectiveness of the proposed Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments (DCNI-HL). The Conventional Localization system achieved an accuracy of 88.7%, indicating that traditional positioning approaches can provide basic patient tracking functionality. However, these systems are highly susceptible to environmental interference, multipath propagation, signal attenuation, and dynamic indoor conditions, which significantly affect positioning reliability.

The Sensor-Based Localization framework improved localization accuracy to 93.5% by incorporating wearable sensors, wireless communication devices, and environmental monitoring technologies. The integration of multiple sensing devices enabled better position estimation and reduced localization uncertainty. Nevertheless, the framework remained sensitive to noisy sensor readings and fluctuations in wireless signal strength.

The Deep Learning Localization model further increased accuracy to 96.8% by automatically learning complex relationships between sensor observations and physical locations. Deep neural networks effectively extracted spatial features from localization data and improved positioning precision. However, the model primarily relied on a single-channel learning strategy, limiting its ability to fully exploit contextual information associated with patient movement and environmental dynamics.

The Proposed DCNI-HL Framework achieved the highest localization accuracy of 99.3%, significantly outperforming all comparative approaches. This superior performance is primarily attributed to the integration of dual-channel feature fusion and neural intelligence learning. The spatial localization channel captured positioning information such as signal strength and distance measurements, while the contextual activity channel incorporated patient behavior, movement patterns, and environmental context. The fusion of these complementary information sources enabled richer feature representations and reduced ambiguity in location

estimation. Furthermore, deep neural learning mechanisms effectively modeled spatial-contextual relationships, allowing the framework to adapt to dynamic assisted living environments and maintain highly accurate patient localization.

Tracking Stability Analysis

Tracking Stability evaluates the consistency of localization predictions during patient movement.

$$TS = \frac{\text{Stable Predictions}}{\text{Total Predictions}} \times 100$$

Table 2. Tracking Stability Comparison

| Model | Stability (%) |
|----------------------------|---------------|
| Conventional Localization | 85.9 |
| Sensor-Based Localization | 91.7 |
| Deep Learning Localization | 95.4 |
| Proposed DCNI-HL | 99.1 |

Dual-channel intelligence enabled highly stable tracking performance even under dynamic environmental conditions. The Table 2 shows, experimental results indicate a substantial improvement in tracking consistency across the evaluated localization approaches. The Conventional Localization system achieved a tracking stability of 85.9%, demonstrating that traditional positioning techniques can monitor patient movement under static conditions but often experience instability when environmental factors such as signal interference, multipath propagation, and patient mobility increase. These issues frequently lead to fluctuating localization outputs and reduced monitoring reliability.

The Sensor-Based Localization framework improved tracking stability to 91.7% through the integration of wearable sensors and environmental monitoring devices. Multiple sensing sources provided additional localization information and helped reduce sudden position variations. However, instability still occurred when sensor readings became noisy or communication signals weakened due to environmental obstacles.

The Deep Learning Localization model further increased tracking stability to 95.4% by learning complex spatial relationships from localization data. Deep neural networks effectively captured movement patterns and environmental dependencies, resulting in smoother localization trajectories and more consistent patient tracking. Nevertheless, the framework primarily relied on single-channel information processing and therefore remained vulnerable to contextual uncertainties.

The Proposed Dual-Channel Neural Intelligence Framework for Healthcare Localization (DCNI-HL) achieved the highest tracking stability of 99.1%, significantly outperforming all comparative methods. This exceptional performance is attributed to the integration of dual-channel intelligence and adaptive neural learning mechanisms. The spatial localization channel continuously monitored signal-based positioning information, while the contextual activity channel captured patient movement behavior and environmental context. By fusing these complementary information sources, the framework effectively minimized localization fluctuations and maintained highly consistent tracking performance. Furthermore, neural intelligence learning enabled adaptive adjustment to changing environmental conditions, ensuring stable localization even in complex assisted living settings.

Conclusion and Discussion

The rapid growth of assisted living environments and intelligent healthcare systems has created an increasing demand for accurate, reliable, and energy-efficient healthcare localization technologies. Continuous patient monitoring, emergency response management, elderly care assistance, and healthcare service optimization all depend on precise indoor localization capabilities. However, conventional localization systems often suffer from signal fluctuations, environmental interference, multipath propagation effects, positioning errors, and limited adaptability to dynamic healthcare environments. To address these challenges, this research proposed a Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments (DCNI-HL) that integrates dual-channel sensor analytics, neural intelligence learning, adaptive feature fusion, and intelligent localization mechanisms for enhanced healthcare monitoring and patient tracking. The proposed framework utilized two complementary information channels to improve localization performance. The first channel focused on spatial localization information, including signal strength measurements, distance estimation, and positioning characteristics. The second channel captured contextual activity information, such as patient movement patterns, environmental conditions, and behavioral indicators. These complementary data sources were processed independently through neural feature extraction mechanisms and subsequently fused to generate robust spatial-contextual representations. Deep neural learning further modeled complex relationships between sensor observations and physical locations, enabling accurate and adaptive localization predictions. From a healthcare perspective, the proposed framework offers significant practical advantages. Accurate patient localization enables healthcare providers to monitor resident activities, detect abnormal movement patterns, support fall prevention systems, improve emergency response effectiveness, and optimize caregiver assistance. Real-time localization information can also facilitate automated healthcare workflows, enhance patient safety,

and reduce operational costs within assisted living facilities. Furthermore, the low latency and energy-efficient characteristics of the proposed framework make it suitable for deployment in wearable healthcare devices, wireless sensor networks, and smart healthcare infrastructures. In conclusion, the proposed Dual-Channel Neural Intelligence Framework for Healthcare Localization in Assisted Living Environments (DCNI-HL) successfully demonstrates the effectiveness of combining dual-channel sensor analytics, neural intelligence learning, and adaptive feature fusion for intelligent healthcare localization. The substantial improvements in localization accuracy, tracking stability, energy efficiency, and response latency highlight the framework's potential as a scalable and reliable solution for next-generation assisted living systems. The research contributes toward the advancement of intelligent healthcare technologies by enabling accurate, automated, and real-time patient localization, ultimately supporting improved healthcare delivery, patient safety, and quality of life.

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