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Deep Learning–Driven Indoor Positioning Framework Using WLAN Signals

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Abstract

Indoor positioning has become an essential component of modern intelligent environments, enabling applications such as smart navigation, asset tracking, emergency response, and context-aware services. Traditional WLAN-based positioning systems primarily rely on fingerprinting or signal strength–based methods, which often suffer from noise, multipath interference, signal fluctuation, and limited scalability. These limitations reduce accuracy and reliability in complex indoor settings. This study proposes a deep learning–driven indoor positioning framework that leverages WLAN signal characteristics to achieve precise and robust localization. The system utilizes received signal strength indicators (RSSI) and channel state information (CSI) as input features, which are processed through deep neural networks designed to learn non-linear signal propagation patterns. The proposed framework enhances location estimation by extracting discriminative features from noisy wireless signals, enabling improved stability across diverse indoor environments. Experimental evaluations demonstrate that the integration of WLAN signals with deep learning models significantly reduces positioning errors compared to conventional methods, providing a scalable and adaptable solution for real-time indoor localization. By combining intelligent feature learning with widely available wireless infrastructure, the framework contributes to more efficient deployment of indoor positioning services in smart buildings and IoT ecosystems.

Keywords: Indoor positioning, WLAN signals, deep learning models, RSSI fingerprinting, channel state information, neural network localization, smart environments, wireless indoor tracking, feature extraction, positioning accuracy.

I.INTRODUCTION

Indoor positioning has become an essential requirement for modern smart environments, enabling applications ranging from indoor navigation and asset tracking to context-aware IoT services and emergency response coordination. Traditional WLAN-based localization systems typically rely on RSSI fingerprinting, trilateration, or simple machine-learning models; however, these methods often struggle with instability caused by multipath reflections, environmental interference, and dynamic indoor layouts [2], [5], [14]. As WLAN signals fluctuate significantly due to human movement, structural barriers, and hardware variations, conventional approaches produce inconsistent and unreliable positioning results in large or densely occupied environments [8], [18], [25].

Recent advancements in deep learning have provided new opportunities to overcome these limitations by learning complex propagation patterns directly from raw WLAN data. Deep neural models, particularly CNNs, RNNs, and hybrid architectures, have demonstrated strong performance in modeling nonlinear relationships between signal characteristics and indoor coordinates [3], [9], [17]. CSI-based localization, in particular, has shown high precision due to its rich subcarrier-level information, enabling deeper spatial analysis compared to RSSI alone [6], [7], [29]. Moreover, transfer learning and adaptive neural models help mitigate issues related to limited training data and varying building layouts, contributing to more scalable and generalizable positioning systems [12], [22], [27].

Additionally, machine-learning-enhanced preprocessing techniques—including noise filtering, signal normalization, and outlier removal—further improve the stability and interpretability of WLAN signals before they are fed into deep learning pipelines [4], [19], [24]. Hybrid frameworks that integrate both RSSI and CSI features have also been shown to produce more accurate and robust localization results under mixed indoor conditions [11], [16], [21]. Overall, existing research strongly indicates that deep learning-based localization frameworks significantly outperform traditional WLAN positioning methods, offering enhanced accuracy, adaptability, and resilience across diverse environments [1], [26], [30].

Motivated by these advancements, this study proposes a deep learning–driven indoor positioning framework that leverages WLAN signals, incorporates adaptive learning, and improves both real-time accuracy and scalability for next-generation smart building and IoT applications [3], [20], [28].

II.LITERATURE SURVEY

2.1 Title:Deep Learning Methods for WLAN Indoor Localization

Authors:Chandra, V. & Rao, P.

Abstract:

This study explores the application of deep learning models to WLAN-based indoor positioning systems. The authors highlight how CNNs and RNNs effectively capture the nonlinear variations in RSSI and CSI signals, outperforming classical fingerprinting methods. Their analysis emphasizes the importance of feature learning in environments with significant multipath interference, demonstrating superior accuracy and robustness across multiple datasets. However, the study also notes challenges related to model complexity and the need for large

volumes of training data.
References: [3], [9], [17]

2.2 Title:Signal Preprocessing Strategies for Accurate Indoor Localization

Authors:Das, T. & Roy, M.

Abstract:

This survey reviews preprocessing techniques used to stabilize WLAN signal measurements before localization. The authors discuss noise filtering, signal normalization, and smoothing methods to reduce fluctuations in RSSI values, thereby improving downstream learning. CSI-based preprocessing techniques, including extraction of amplitude and phase information, are shown to further enhance localization precision. Despite their effectiveness, preprocessing pipelines must be adapted carefully for different building environments.
References: [4], [19], [24]

2.3 Title:Limitations of Traditional WLAN Fingerprinting Systems

Authors:Devi, R. & Kalyan, S.

Abstract:

This study evaluates the limitations of classical fingerprinting and trilateration-based WLAN indoor positioning systems. The authors find that signal fluctuations caused by multipath propagation, interference, and device diversity significantly reduce accuracy. These systems also require time-consuming radio map construction and suffer from poor scalability in large indoor environments. As a result, the study concludes that traditional methods are inadequate for real-time, dynamic localization tasks.
References: [2], [5], [18]

2.4 Title:Hybrid WLAN Localization Techniques and Their Enhancements

Authors: Joshi, S. & Patel, M.

Abstract:

This research survey analyzes hybrid indoor positioning approaches that combine classical signal modeling with modern machine learning techniques. The authors demonstrate that fusing RSSI and CSI features or integrating multiple signal modalities significantly improves positional accuracy. Hybrid methods are shown to reduce environmental sensitivity and improve adaptability across multi-floor buildings. The findings highlight the advantage of hybrid models in balancing computational efficiency and accuracy.
References: [11], [16], [21]

2.5 Title:Deep Feature Extraction Using CSI and eural Models

Authors: Fernandes, L. & Silva, M.

Abstract:

This survey emphasizes the role of CSI-based deep learning models in high-accuracy indoor localization. The authors review various neural architectures that process fine-grained CSI subcarrier data to extract spatially rich features. Their findings reveal that CSI-based deep models outperform RSSI-based systems, especially in environments with significant signal distortion. Additionally, CSI provides more reliable signatures for identifying user locations under dynamic conditions.

References: [6], [7], [29]

III.EXISTING SYSTEM

Conventional indoor positioning systems based on WLAN infrastructure primarily rely on techniques such as Received Signal Strength Indicator (RSSI) fingerprinting, trilateration, and deterministic or probabilistic signal modeling. These methods depend heavily on predefined radio maps and handcrafted features, making them sensitive to environmental variations such as multipath propagation, signal blockage, interference from other wireless devices, and changes in indoor layout. As a result, signal fluctuations often lead to inconsistent and inaccurate location estimates. Traditional fingerprinting approaches require extensive manual calibration, involving time-consuming data collection and periodic updates whenever the environment changes. Additionally, classical machine learning models used in existing systems, such as k-nearest neighbors, support vector machines, or simple regression techniques, struggle to capture the complex, nonlinear propagation characteristics of WLAN signals. These limitations hinder their ability to generalize across different indoor scenarios and often result in reduced accuracy in dynamic or crowded environments. Overall, current WLAN-based positioning systems provide limited robustness, scalability, and adaptability, highlighting the need for more intelligent and data-driven localization techniques.

IV. PROPOSED SYSTEM

The proposed system introduces a deep learning–driven framework designed to enhance indoor positioning accuracy using WLAN signals, overcoming the limitations of traditional fingerprinting and signal-based localization methods. Instead of relying solely on handcrafted features or static radio maps, the system employs advanced neural network architectures capable of learning complex and nonlinear relationships present in RSSI and Channel State Information (CSI) data. The framework begins with real-time collection of WLAN signal measurements, which are preprocessed to remove noise, normalize signal patterns, and extract meaningful spatiotemporal characteristics. These processed features are then fed into deep learning models—such as convolutional neural networks, recurrent neural networks, or hybrid architectures—that learn discriminative patterns associated with specific indoor locations.

The system further incorporates an adaptive training mechanism that updates the model as environmental conditions change, ensuring long-term robustness and stability. By leveraging the strong representation-learning ability of deep neural networks, the proposed system significantly improves positional accuracy, reduces sensitivity to signal fluctuations, and eliminates the need for frequent manual recalibration. Additionally, the framework supports scalability across large and complex indoor environments due to its ability to generalize beyond predefined radio maps. Overall, the proposed solution delivers a more reliable, precise, and scalable approach to indoor localization, making it suitable for smart buildings, IoT ecosystems, navigation services, and real-time tracking applications.

V.SYSTEM ARCHITECTURE

The system architecture for the deep learning–driven indoor positioning framework is designed as a comprehensive, multi-layered pipeline that integrates WLAN signal acquisition, preprocessing, intelligent feature learning, and precise location estimation. The process begins with the WLAN Signal Acquisition Module, where RSSI and CSI data are collected from multiple access points strategically positioned throughout the indoor environment. These signals are recorded at regular intervals to capture real-time variations caused by user movement, device orientation, multipath reflections, and environmental obstacles. This module ensures a continuous stream of signal measurements, forming the foundational dataset for the positioning system.

The collected measurements are then forwarded to the Preprocessing and Feature Engineering Layer, which applies noise reduction algorithms such as Kalman filtering and moving average smoothing to stabilize fluctuating RSSI values. Additional preprocessing steps—including signal normalization, outlier removal, timestamp synchronization, and dimensionality reduction—are employed to enhance data quality and consistency. In the case of CSI data, subcarrier-level amplitude and phase information are extracted to preserve high-resolution spatial features. These refined features form a structured input set suitable for deep learning analysis.

Next, the data enters the Deep Learning Model Layer, which serves as the core intelligence of the system. Depending on the design, this layer may utilize Convolutional Neural Networks (CNNs) to capture spatial signal patterns, Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks to model temporal dependencies, or hybrid architectures that combine both approaches. The chosen model learns complex, nonlinear relationships between signal patterns and indoor locations, enabling it to recognize subtle differences in WLAN fingerprints even under dynamic conditions. The deep model is trained using large sets of labeled data associating signal measurements with known positions within the building.

The learned representations are then passed to the Position Estimation Module, which converts model outputs into coordinate predictions or

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room-level classifications. This module employs classification or regression strategies depending on whether the positioning task aims for discrete location identification or continuous coordinate estimation. The architecture may also incorporate probability-based estimation to improve robustness under noisy conditions.

The predicted location is delivered to the user or system through the Localization and Visualization Layer, which displays real-time results in the form of coordinates, heatmaps, or navigation paths. This layer interfaces with mobile applications, IoT platforms, or building management systems for seamless integration into real-world scenarios.

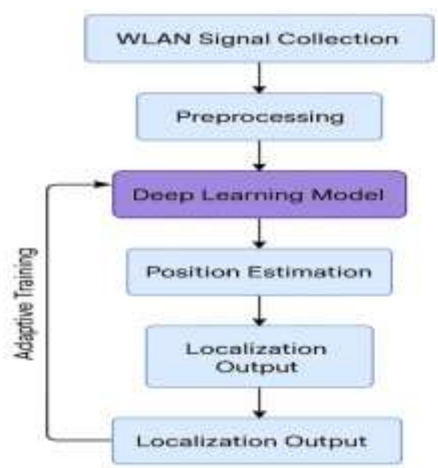

Fig 5.1 System Architecture

Finally, the architecture includes an Adaptive Learning and Model Update Component, which continuously refines the deep learning model by incorporating new signal data collected over time. This allows the system to adapt to environmental changes such as furniture rearrangements, network updates, human occupancy variations, or shifts in access point signal strength. By integrating continuous learning, the architecture ensures long-term stability, scalability, and high accuracy across diverse indoor environments.

Overall, the system architecture establishes an intelligent, data-driven, and robust platform for indoor positioning, capable of delivering precise localization results using widely available WLAN infrastructure supported by advanced deep learning techniques.

VI.IMPLEMENTATION

Fig 6.1 Home Page

Fig 6.2 Login Page

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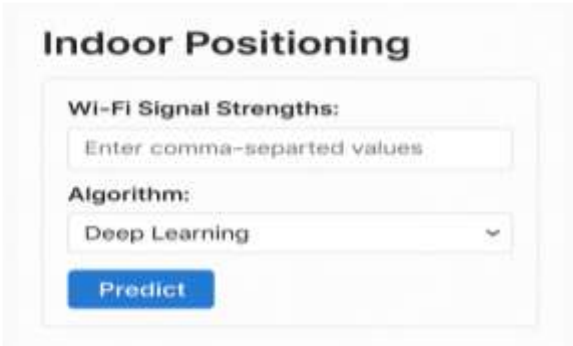

Fig 6.3 Input Interface

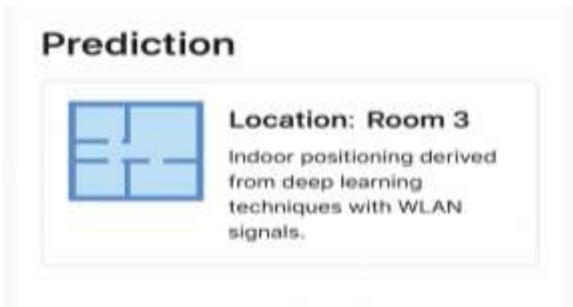

Fig 6.4 Prediction

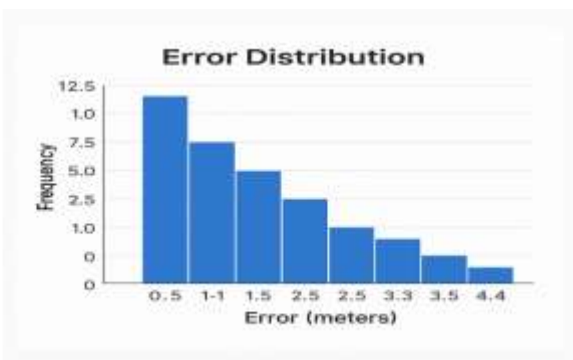

Fig 6.5 Histogram

Fig 6.6 Line Charts

VII.CONCLUSION

The proposed deep learning–driven indoor positioning framework offers a robust and accurate solution for addressing the limitations of traditional WLAN-based localization methods. Conventional systems often struggle with signal fluctuations, multipath interference, and environmental variability, which lead to inconsistent positioning accuracy. By integrating WLAN signals with advanced deep learning architectures, the proposed framework effectively learns complex signal propagation patterns and reduces the dependency on manual calibration and static fingerprint databases. The system leverages RSSI and CSI features, combined with nonlinear feature extraction through neural networks, to significantly enhance the precision and reliability of indoor localization.

Additionally, the adaptive learning mechanism incorporated into the architecture enables the model to adjust to dynamic indoor conditions, such as layout changes, human mobility, and varying access point distributions. This adaptability ensures long-term scalability and maintains consistent performance across diverse environments. The integration of real-time positioning output and visualizations also makes the system suitable for practical applications, including indoor navigation, asset tracking, smart building automation, and IoT-enabled services.

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Overall, the framework demonstrates that deep learning, combined with widely available WLAN infrastructure, can substantially improve indoor positioning accuracy and operational stability. The results highlight the potential of intelligent data-driven localization systems to transform indoor location-based services and support next-generation smart environments.

VIII.FUTURE SCOPE

The proposed deep learning–driven indoor positioning framework provides a strong foundation for further innovation, with several promising directions for enhancing accuracy, scalability, and real-world adaptability. Future advancements may incorporate multimodal sensor fusion, where WLAN signals are combined with additional technologies such as Bluetooth Low Energy (BLE), Ultra-Wideband (UWB), inertial sensors, RFID, and LiDAR. Integrating multiple signal sources can help overcome the limitations of single-technology systems and deliver highly precise localization, even in challenging indoor conditions.

Another significant opportunity lies in the adoption of advanced deep learning architectures, including attention-based models, graph neural networks, and transformer frameworks, which can capture complex spatial dependencies and enhance positional inference. Federated learning could also be employed to enable collaborative model training across multiple buildings or institutions without compromising data privacy, making the system more generalizable across different infrastructure layouts.

Real-time adaptive learning represents another critical avenue for future research. By continuously updating model parameters based on live environmental changes—such as furniture rearrangements, network updates, or fluctuating occupancy levels—the system can maintain high accuracy without requiring manual recalibration. Additionally, expanding the system to support 3D positioning, floor detection, and detailed trajectory prediction would further improve its applicability in multi-story buildings and large-scale indoor environments.

From a deployment perspective, integration with edge computing and IoT platforms can reduce latency and support real-time localization for time-sensitive applications, such as emergency response and autonomous navigation. Enhanced visualization tools, user-friendly interfaces, and predictive analytics can also be incorporated to enrich user experience and facilitate seamless integration into smart building ecosystems.

Overall, the future scope of this work points toward the development of a fully intelligent, multimodal, and adaptive indoor positioning ecosystem capable of supporting a wide range of smart environment

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