electronics

Review

Machine Learning Integration in Ultra-Wideband-Based Indoor Positioning Systems: A Comprehensive Review

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Abstract

Ultra-Wideband (UWB) technology enables centimeter-level indoor positioning, but it remains highly sensitive to channel dynamics, multipath and Non-Line-of-Sight (NLoS) propagation. Recent studies increasingly apply Machine Learning (ML) methods to address these issues by modeling nonlinear channel behavior and mitigating ranging bias. This paper presents a comprehensive review and provides a critical synthesis of 169 research works published between 2020 and 2024, offering an integrated overview of how ML techniques are incorporated into UWB-based Indoor Positioning Systems (IPSs). The studies are grouped according to their functional objective, learning algorithm, network architecture, evaluation metrics, dataset, and experimental setting. The results indicate that most approaches apply ML to channel classification and ranging error mitigation, with Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and hybrid CNN–Long Short-Term Memory (LSTM) architectures being among the most common choices due to their ability to capture spatial and temporal patterns in the Channel Impulse Response (CIR). Despite the reported accuracy improvements, scalability and cross-environment generalization remain open challenges, largely due to the scarcity of public datasets and the lack of standardized evaluation protocols. Emerging research trends highlight growing interest in transfer learning, domain adaptation, and federated learning, along with lightweight and explainable models suitable for embedded and multi-sensor systems. Overall, this review summarizes the progress made in ML-driven UWB localization, identifies current gaps, and outlines promising directions toward more robust and generalizable indoor positioning frameworks.

Keywords: ultra-wideband; indoor positioning; machine learning; deep learning; channel impulse response; non-line-of-sight classification; ranging error mitigation; transfer learning

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1. Introduction

Short-range wireless technologies designed for low power consumption and moderate data rates have been used for many years in personal and local area networks. Examples include Bluetooth Low Energy (BLE), Zigbee, Wi-Fi, and Ultra-Wideband (UWB), which provide reliable and energy-efficient short-range communication. Among them, UWB stands out for its very precise ranging and localization based on Time-of-Flight (ToF) measurements. Although UWB was originally developed for short-range data transmission, it has recently become one of the most promising technologies for high-accuracy indoor positioning [1]. Its precision mainly comes from the availability of physical-layer parameters such as Received Signal Strength (RSS), ToF, and Channel Impulse Response (CIR), which offer detailed signal information useful for estimating distances and positions in indoor environments. For this reason, UWB is now considered a key technology for accurate and reliable indoor localization systems.

Given the increasing interest in accurate indoor positioning, several technologies have been proposed to implement Indoor Positioning Systems (IPSs), which estimate the position of objects or users inside buildings, where satellite-based systems such as Global Positioning System (GPS) do not work properly. Among the available wireless options, UWB has become in recent years the most accurate solution for indoor localization, offering much higher precision than other short-range alternatives such as BLE, Wi-Fi, or Zigbee. Under normal conditions, UWB provides sub-meter accuracy, and in optimized Line-of-Sight (LoS) scenarios it can reach centimeter-level precision, as demonstrated in several experimental studies [2]. Comparative works have also confirmed that it generally performs better than other modern wireless positioning technologies in terms of accuracy [3]. Moreover, large-scale deployments with multiple tags have shown high precision and reliability, demonstrating the maturity of UWB-based IPSs for real-world indoor localization [4].

Although UWB-based positioning provides high accuracy, it still faces several challenges in real-world environments. As with other radio-based systems, multipath propagation, Non-Line-of-Sight (NLoS) conditions, antenna orientation, and the presence of obstacles or moving people can cause significant ranging errors. In severe NLoS situations, these errors can even exceed one meter. Traditional geometry-based positioning methods estimate distances or angles from signal parameters such as ToF or Time Difference of Arrival (TDoA), and then compute the coordinates through multilateration or triangulation. However, under NLoS or multipath conditions, these approaches are very sensitive to distorted signal paths and inaccurate range measurements, which can lead to biased position estimates.

To address these limitations, hybrid solutions have been proposed, for example, by combining UWB with Inertial Measurement Unit (IMU) sensors, in order to improve robustness and maintain reasonable accuracy even in difficult conditions [5–7]. However, although sensor-fusion strategies enhance robustness, they still depend on explicit geometric models and traditional signal processing steps. These approaches often struggle to adapt to different environments or hardware setups. In recent years, data-driven methods based on Machine Learning (ML) have been investigated as a promising alternative [8,9]. Several studies have used signal features such as the CIR to capture complex propagation effects and estimate positions directly [10].

These challenges have increased the interest in ML as an alternative to traditional signal processing and geometry-based positioning methods. Instead of depending only on predefined propagation models, ML techniques can use channel information such as the CIR or other parameters derived from the received signal, including RSS and ToF. Early research applied ML to identify LoS/NLoS conditions, helping to improve data selection and reduce bias in geometric solvers [8]. Later works explored regression and neural models to correct ranging errors before multilateration or triangulation, thus improving robustness under challenging propagation conditions [6,9]. More recently, ML-based fingerprinting and feature-matching methods have been used to estimate user positions directly from channel features, achieving competitive accuracy even in complex indoor environments [10,11].

In recent years, there has been a clear growth in publications exploring the intersection between UWB and ML, as illustrated in Figure 1. This reflects a broader trend towards integrating data-driven methods into communication and localization systems. The bibliometric data were obtained from Scopus using the same query described in Section 4, that is, the exact search string combining Ultra-Wideband, Machine Learning, and indoor positioning-related terms. The search was applied to titles, abstracts, and author keywords, covering all document types indexed in Scopus between 2004 and 2024. Before 2018, publications explicitly combining UWB and ML were quite limited, since most studies still depended on traditional model-based signal processing and localization methods. The clear increase after 2018 coincides with the availability of open UWB datasets and the spread of Deep Learning (DL) architectures, which enabled data-driven analysis of channel features and localization performance. As shown in the figure, the number of publications started to rise significantly after 2018 and more than doubled between 2020 and 2024, showing the fast convergence of UWB and ML research. This growing trend highlights the increasing importance of this intersection and supports the need for a comprehensive overview of current works and open challenges.

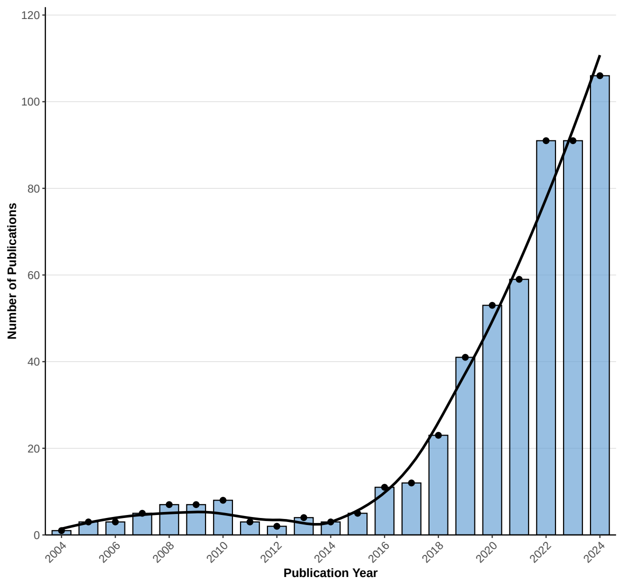

Figure 1. Number of publications per year found in Scopus using the same query explained in the methodology section. The search included all types of documents that combine UWB and ML in the field of indoor positioning. The trend line corresponds to a LOESS curve (Locally Estimated Scatterplot Smoothing), a non-parametric local regression used to highlight the overall growth pattern. The strong increase in recent years shows the rising interest in this topic and the motivation for carrying out a comprehensive review.

Despite the increasing number of studies, to the best of our knowledge, no comprehensive review has yet examined the intersection of UWB and ML in a clear and structured way. Existing surveys have discussed specific aspects of UWB-based localization or focused on popular topics in positioning research for Wi-Fi, BLE, or general indoor systems. However, none of them have systematically analyzed how ML can be applied throughout the entire UWB positioning pipeline, from channel condition classification to ranging error correction and position estimation. UWB systems are fundamentally different from other short-range technologies in their signal structure (for example, wide bandwidth and high time resolution) and in the availability of rich physical-layer features such as CIR and ToF. These characteristics introduce specific ML challenges, including multipath characterization, NLoS detection, and range error mitigation. Overall, this study is framed as a comprehensive review conducted using a systematic methodology, enabling a structured and reproducible assessment of ML contributions to UWB-based indoor positioning.

Specifically, this paper aims to:

- Identify and categorize the main UWB-related tasks where ML models are applied to improve indoor positioning accuracy and robustness.
- Review the most common ML models and architectures used for UWB-based localization and signal processing.
- Summarize the evaluation metrics and experimental setups reported in UWB–ML research for performance analysis.
- Highlight the main limitations and open challenges found in the literature, providing directions for future studies on UWB–ML integration.

This review provides a structured and reproducible overview of the current state of the field, aiming to help both researchers and practitioners to advance high-accuracy IPSs.

Overall, the analysis indicates that most studies applying ML to UWB localization focus on channel condition classification and ranging error correction, while a smaller but growing number address position estimation. DL architectures, especially Convolutional Neural Networks (CNNs), Long Short-Term Memoriess (LSTMss), and hybrid models, dominate recent work due to their ability to model spatio-temporal dependencies in the CIR. However, reproducibility and cross-environment generalization remain open challenges, mainly due to the limited number of open datasets and the absence of standardized evaluation benchmarks.

The remainder of this paper is organized as follows. Section 2 reviews existing surveys and highlights the specific gap that this work aims to fill. Section 4 describes the review methodology used to ensure a comprehensive and unbiased analysis. The main results are presented in Section 5, where both quantitative and qualitative answers to the research questions are discussed. Section 6 analyzes these results, highlighting the main trends, limitations, and implications for the field. Finally, Section 7 concludes the paper and proposes a roadmap with clear directions for future research toward robust and intelligent UWB-based positioning systems.

2. Related Work

Indoor positioning has been widely reviewed during the last decade, although existing surveys differ in their scope, methodology, and application focus. To provide a clear context for this review, the related literature is organized into a logical narrative sequence. We begin by positioning UWB within the broader landscape of alternative indoor positioning technologies to highlight its distinct advantages. Subsequently, we analyze broad IPS surveys that encompass UWB, followed by a review of early UWB-specific studies and general ML-focused surveys. Finally, recent domain-specific UWB reviews are examined. This organization serves to identify the specific gap where the intersection between modern ML techniques and the complete UWB positioning pipeline remains unexplored.

2.1. Overview of Alternative Indoor Positioning Technologies

While this review focuses on UWB, it is important to contextualize its role within the broader landscape of indoor positioning technologies. A wide range of physical media have been explored by researchers, including radio-frequency-based, optical, magnetic, and acoustic signals, as discussed in general surveys [12,13]. Each technology exhibits distinct propagation characteristics and limitations, where ML is increasingly employed to improve robustness and accuracy.

Visible Light Communication (VLC) systems exploit Light-Emitting Diode (LED)-based lighting infrastructure to enable high-precision indoor positioning. Recent comprehensive surveys highlight the growing role of ML and DL in compensating for non-linear optical channels [14], while specific neural network-based approaches have been applied to optimize energy efficiency in Simultaneous Lightwave Information and Power Transfer (SLIPT)-enabled frameworks [15]. However, unlike UWB, VLC positioning remains strongly constrained by LoS conditions.

Magnetic-based localization exploits disturbances in the Earth's magnetic field or actively generated Magneto-Inductive (MI) fields. These techniques are particularly suitable for underground or radio-denied environments. In this context, ML is commonly applied through fingerprinting and pattern recognition to handle the non-uniqueness of magnetic signatures [13]. Despite their robustness to NLoS, such systems typically offer shorter operational ranges than UWB.

Wi-Fi and BLE technologies are among the most widely deployed solutions for indoor positioning due to their low deployment cost and existing infrastructure. However, they suffer from significant signal variability and multipath effects. As a result, ML-based fingerprinting techniques are extensively used to model complex propagation patterns, although the achievable positioning accuracy (typically 1–5 m) remains lower than that of UWB systems [16].

Table 1 provides a summary comparison of these technologies, highlighting their operating principles, typical accuracy, and the primary role of ML in enhancing their performance.

Table 1. Comparison of indoor positioning technologies and the role of ML.

Technology	**Mechanism**	**Accuracy**	**Main ML Application**
UWB	ToF/TDoA/AoA	Centimeter-level	NLoS classification, bias mitigation, and direct pulse processing.
Wi-Fi/BLE	RSS/CSI Fingerprinting	Meter-level	Learning complex signal maps to handle fluctuations [16].
VLC	RSS/AoA (Optical)	Centimeter-level	Channel modeling, non-linearity compensation, and energy optimization [14].
Magnetic/MI	Field Strength/Anomalies	Meter-level	Pattern matching and anomaly detection for magnetic signatures.
Acoustic	ToF (Sound)	Centimeter-level	Echo classification and reverberation mitigation.

2.2. Broad IPS Surveys Including UWB

Several surveys have taken a broader view, covering different indoor positioning technologies. For instance, Zafari et al. [12] and Mendoza-Silva et al. [13] proposed taxonomies that include Wi-Fi, BLE, ZigBee, UWB, and other systems. However, in these earlier surveys, UWB is often discussed at a high level without focusing on its distinct signal structure. This gap is addressed in very recent high-impact surveys. Santra et al. [17] extensively review ML for radio frequency sensing, covering radar and Wi-Fi in depth while providing valuable context for UWB integration. Complementing this, Fischer et al. [18] provide a comprehensive analysis of angular-based localization technologies in 2025, comparing UWB against Acoustic and 5G/6G systems. Similarly, Umer et al. [19] explore the integration of UWB within the 6G ecosystem, specifically focusing on Reconfigurable Intelligent Surface (RIS)-assisted localization. Unlike general reviews, these recent contributions highlight the increasing convergence of UWB with beamforming and intelligent surfaces.

2.3. Early UWB-Focused Surveys

One of the first and most influential surveys in the field was published by Alarifi et al. [20], providing a broad overview of indoor positioning methods with a dedicated section on UWB. Beyond proposing a useful taxonomy, that work applied a strengths, weaknesses, opportunities, and threats (SWOT) analysis, a framework seldom utilized in this domain, to evaluate the relative merits of different technologies. Similarly, Mazhar et al. [21] reviewed UWB-based positioning in comparison with narrowband systems, discussing both algorithmic foundations and practical implementation challenges. Although these early papers provide essential insights into UWB fundamentals, their focus remains primarily on hardware and geometric algorithmic aspects, with only limited discussion of ML-based methods. More recently, Ridolfi et al. [22] presented a detailed review of UWB self-calibration and collaborative localization methods. However, while it offers an extensive overview of system architectures, it continues to rely on traditional geometry-based solvers and does not explore the emerging field of data-driven or ML-based approaches.

2.4. ML-Focused Surveys in IPS

One of the first surveys to explicitly examine the role of ML in indoor positioning was published by Nessa et al. [16], who reviewed algorithms such as Support Vector Machine (SVM), Random Forest (RF), CNN, and LSTMs across different IPS applications. This work highlighted the potential of ML to improve positioning performance. However, UWB was only mentioned briefly and not analyzed in detail. Therefore, although ML is now widely recognized as an important technology for IPS, its application to UWB-based systems is still not well explored.

2.5. Recent UWB Surveys in Specific Domains

Several recent reviews have brought the attention back to UWB, often focusing on specific domains or application areas. For example, Elsanhoury et al. [23] analyzed the use of UWB in logistics and industrial navigation, mentioning ML only briefly and without proposing a clear taxonomy. Wang et al. [24] concentrated exclusively on NLoS identification and mitigation, comparing classical and ML-based methods, but this narrow scope covers only one stage of the IPS pipeline. In a broader context, Hapsari et al. [25] applied systematic mapping techniques to discuss open challenges in UWB tag localization, yet without explicitly connecting them to ML-driven solutions. Lastly, Al-Okby et al. [26] reviewed real-time UWB modules and systems, focusing mainly on hardware characteristics and descriptive comparisons, with only limited reference to ML integration.

Table 2 summarizes the main characteristics of the reviewed surveys. Overall, existing reviews can be grouped into three categories: those focused on UWB but not on ML, those centered on ML with little attention to UWB, and a few recent works combining both but limited to specific tasks such as NLoS detection. In contrast, this review provides a holistic perspective by covering the entire positioning pipeline and the reproducibility aspects often neglected in previous studies.

Some surveys also use structured approaches such as strengths, weaknesses, opportunities, and threats analysis or systematic mapping, offering additional perspectives on UWB positioning. However, their scope is still limited and they do not provide an integrated taxonomy linking ML methods with UWB-specific tasks along the IPS pipeline. Moreover, reproducibility aspects, such as datasets and evaluation metrics, are rarely discussed in depth.

Against this background, while previous surveys have addressed important aspects of indoor positioning, several areas for further analysis remain. Early UWB-focused reviews largely predate the widespread adoption of DL techniques, whereas broader IPS surveys often consider UWB at a high level, without fully exploiting its distinctive CIR-level characteristics. Moreover, recent ML-oriented surveys tend to focus on isolated tasks, such as NLoS detection or ranging correction, leaving an opportunity for a more holistic view of how learning-based components integrate across the full positioning pipeline. Furthermore, reproducibility aspects, including the availability of public datasets and standardized evaluation protocols, are often discussed only briefly.

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Table 2. Comparison of representative survey papers related to indoor positioning and UWB-based localization, highlighting their coverage of ML, datasets, and evaluation aspects.

Article	Year	UWB	ML	LoS/NLoS	CIR Use	Fusion/Hybrid	Dataset	Metrics
Alarifi et al. [20]	2016	✓	✗	✗	✗	✗	✗	∼
Mazhar et al. [21]	2017	✓	✗	✗	✗	✗	✗	∼
Zafari et al. [12]	2019	✓	✗	✗	✗	✗	✗	∼
Mendoza-Silva et al. [13]	2019	✓	✗	✗	✗	✗	✗	✗
Nessa et al. [16]	2020	∼	✓	✗	✗	✗	✗	✓
Ridolfi et al. [22]	2021	✓	✗	∼	∼	∼	✗	∼
Elsanhoury et al. [23]	2022	✓	∼	✗	✗	✗	✗	✗
Wang et al. [24]	2023	✓	✓	∼	✗	✗	✗	✓
Hapsari et al. [25]	2024	✓	∼	✗	✗	✗	✗	✗
Al-Okby et al. [26]	2024	✓	∼	✗	✗	✗	✗	∼
Santra et al. [17]	2025	✓	✓	∼	∼	✓	✗	∼
Fischer et al. [18]	2025	✓	∼	✓	✗	✓	✗	✓
Umer et al. [19]	2025	✓	✓	✓	∼	✓	✗	∼
This review	2025	✓	✓	✓	✓	✓	✓	✓

Symbols: ✓ = Covered in detail; ∼ = Partially covered; ✗ = Not addressed.

Motivated by these observations, the present review provides a structured analysis of the intersection between ML and UWB-based indoor positioning. By following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, this work aims to minimize selection bias and provide a transparent, reproducible synthesis of recent literature. This effort seeks to complement earlier reviews by bridging the gap between isolated algorithmic improvements and a comprehensive understanding of current trends, methodological choices, and open challenges in data-driven UWB systems.

3. Background

3.1. Common UWB Localization Schemes

Due to its large bandwidth and nanosecond-level temporal resolution, UWB technology enables localization schemes that are difficult to achieve with narrowband systems. These are commonly classified into range-based (geometric) methods and fingerprinting-based approaches, with hybrid configurations as an extension.

Range-based (time-based) schemes estimate distances by exploiting precise time measurements. The most common approaches are ToF and Two-Way Ranging (TWR), where distance is derived from round-trip signal propagation. For large-scale deployments, TDoA is widely adopted, as it allows high scalability at the cost of requiring tight synchronization among anchors, as demonstrated in systems like uLoc [4]. Experimental studies have shown that these methods can achieve centimeter-level precision in optimized scenarios [2].

Angle-based schemes, such as Angle of Arrival (AoA) or Phase Difference of Arrival (PDoA), estimate the direction of arrival using multi-antenna arrays. These techniques enable localization with fewer anchors, including single-anchor configurations, although they are sensitive to device orientation and hardware complexity [1,11].

Fingerprinting-based schemes avoid explicit geometric modeling by mapping signal features to locations. In UWB systems, fingerprinting typically exploits the rich structure of the CIR rather than simple signal strength, which is particularly effective for direct position estimation in complex environments [10].

Finally, hybrid schemes combine multiple approaches, such as UWB with IMU sensors, to improve robustness and maintain accuracy even in difficult NLoS conditions [5–7]. Most ML-based methods reviewed in this paper aim to mitigate the limitations inherent to these localization schemes [9].

3.2. UWB Signal Model and CIR

UWB systems are characterized by the transmission of very short pulses with large bandwidth, enabling fine temporal resolution of the propagation channel. The received signal can be modeled as a superposition of delayed and attenuated replicas of the transmitted pulse:

$$r(t) = \sum_{k=1}^{K} \alpha_k s(t - \tau_k) + n(t), \tag{1}$$

where $s(t)$ represents the transmitted pulse waveform, α_k and τ_k denote the attenuation and delay of the k-th multipath component, respectively, and $n(t)$ represents additive white Gaussian noise.

The sampled CIR, $h[n]$, provides rich information about multipath propagation and constitutes the main physical observable exploited by UWB-based localization systems to distinguish between the direct path and reflections.

3.3. UWB Ranging Principles

Distance estimation in UWB systems is commonly based on the ToF of the transmitted signal. Due to the lack of perfect clock synchronization between devices, TWR protocols are widely adopted.

In particular, Double-Sided Two-Way Ranging (DS-TWR), implemented in commercial UWB transceivers such as the Decawave DW1000, mitigates clock drift by exchanging multiple messages between the anchor and the tag. The propagation time is computed as:

$$T_{\text{prop}} = \frac{T_{\text{round1}} T_{\text{round2}} - T_{\text{reply1}} T_{\text{reply2}}}{T_{\text{round1}} + T_{\text{round2}} + T_{\text{reply1}} + T_{\text{reply2}}}, \tag{2}$$

and the estimated distance is obtained as $d = c\, T_{\text{prop}}$, where c denotes the speed of light.

3.4. NLoS Error Modeling in UWB Systems

In ideal LoS conditions, the measured distance closely matches the true Euclidean distance. However, in indoor environments, NLoS conditions introduce a positive bias due to signal obstruction and multipath propagation. The distance measurement can be modeled as:

$$d = \begin{cases} d_{\text{true}} + e_M, & \text{LoS} \\ d_{\text{true}} + e_M + e_N, & \text{NLoS} \end{cases} \tag{3}$$

where e_M represents zero-mean measurement noise and e_N denotes the NLoS-induced bias ($e_N > 0$), commonly modeled as a non-Gaussian random variable (e.g., exponential or log-normal distribution).

Accurate identification and mitigation of e_N constitute one of the main challenges in UWB indoor localization.

3.5. Position Estimation Algorithms

Given distance estimates to N anchors with known coordinates $\mathbf{p}_i$, the position $\mathbf{p}$ of the tag can be obtained by solving a multilateration problem. A common approach is Weighted Least Squares (WLS), formulated as:

$$\hat{\mathbf{p}} = \arg\min_{\mathbf{p}} \sum_{i=1}^{N} w_i (\|\mathbf{p} - \mathbf{p}_i\| - d_i)^2, \tag{4}$$

where the weights w_i reflect the reliability of each range measurement. For mobile targets, recursive Bayesian estimators such as the Extended Kalman Filter (EKF) are often employed to fuse temporal information and reduce noise.

3.6. ML for UWB Channel and Error Modeling

Recent approaches leverage ML to exploit the rich information contained in the UWB channel impulse response. Instead of relying solely on threshold-based detectors, ML models learn a nonlinear mapping:

$$\hat{b}_{\mathrm{NLoS}} = f_\theta(\mathbf{f}_{\mathrm{CIR}}), \tag{5}$$

where $\mathbf{f}_{\mathrm{CIR}}$ denotes features extracted from the CIR (e.g., delay spread, kurtosis, rise time, or even raw samples), and f_θ represents a trained model with parameters θ.

The estimated bias can be used to correct range measurements or to adaptively weight them in the position estimation stage, effectively integrating physical-layer channel modeling with data-driven inference.

4. Research Methodology

This work is structured as a comprehensive review conducted using a systematic methodology, following PRISMA (2020) guidelines [27] for the search, selection, and organization of the analyzed studies. To ensure methodological transparency and adherence to international standards, the full PRISMA 2020 Checklist is provided as Supplementary Materials. Although the review draws inspiration from the PRISMA framework, the emphasis is placed on integrating and interpreting the available research rather than applying a strictly systematic protocol. The methodology includes the definition of research questions, the formulation of database queries, the application of Inclusion Criteria (IC) and Exclusion Criteria (EC), and the structured extraction of relevant information from each selected study.

The use of this structured approach is motivated by its clarity and reproducibility, which help to ensure a consistent and transparent analysis of the literature. Following the general principles of PRISMA, the review process included the main phases of identification, screening, eligibility, and inclusion. This procedure helps to maintain transparency in the search and selection of relevant works.

In line with these steps, the process followed in this study can be summarized as follows:

1. Definition of the Research Questions (RQs), to delimit the scope and objectives of the review.
2. Specification of IC and EC, to decide whether a study is relevant for the analysis.
3. Search in scientific databases (Scopus and Web of Science (WoS)) using advanced queries that combine key terms related to UWB, ML, and indoor positioning.
4. Screening of the retrieved articles, removing duplicates and applying the IC and EC to titles, abstracts, and keywords, followed by a full-text review.
5. Extraction and synthesis of information from the selected studies, organizing key aspects such as publication year, ML tasks, algorithms, evaluation metrics, experimental setups, and reported results.

Further details about the research questions and the IC/EC are provided in Sections 4.1 and 4.2. The overall selection process is also summarized using a PRISMA-inspired flow diagram, which shows the number of records identified, screened, and finally included in the review (see Section 4.4).

4.1. Research Questions

Defining clear research questions is an essential step in any comprehensive review, as it helps to delimit the scope and objectives of the analysis. In this work, one Main Research Question (MRQ) is proposed to address the topic at a general level, followed by several specific RQs that guide the organization of information and the synthesis of results.

MRQ. How do ML algorithms contribute to UWB-based IPSs?

RQ1. What specific tasks or functions within the pipeline of UWB-based IPSs are addressed through ML algorithms?

RQ2. Which ML algorithms are most commonly applied to these tasks, and what motivations or advantages are reported in the literature to justify their use?

RQ3. How are ML-based UWB positioning methods evaluated in terms of experimental design, performance metrics, validation procedures, and reproducibility?

RQ4. What public datasets or benchmarks are available for combining UWB and ML, and how are they used to improve the reproducibility and comparability of results?

RQ5. What are the main challenges, limitations, and open issues identified in applying ML to UWB-based indoor positioning, and what directions for future research are suggested?

These research questions define the general structure of the review and are addressed progressively throughout the analysis. Their answers are presented in Section 5 and further discussed in Section 6, ensuring that they remain central to the interpretation of the literature.

4.2. Inclusion and Exclusion Criteria

To make sure that the studies considered in this review are relevant and reliable, a set of IC and EC was defined. These criteria are consistent with the objectives of the review and were applied during the screening and evaluation stages. This approach helped to focus the analysis on studies that provide meaningful evidence of how ML is applied in UWB-based IPSs, while excluding works with limited relevance to this topic.

IC1. The study must be a primary research article published in a peer-reviewed journal or conference proceedings. Secondary papers, such as reviews, surveys, or tutorials, were not considered.

IC2. The study must be written in English, as this review only includes articles available in that language.

IC3. The study must involve the use of UWB technology for indoor positioning and apply ML algorithms in a way that has a direct impact on the system's performance.

EC1. Studies where UWB was not a central component for estimating positioning-related parameters, such as location, heading, tracking, NLoS mitigation, or coordinate-level fusion, were not included. Works in which UWB was used only marginally, in a comparative way, or for other purposes unrelated to indoor positioning (e.g., payment systems, door access, or in-vehicle navigation) were excluded.

EC2. Studies where the use of ML was only marginal were also excluded. For example, papers that applied ML only to auxiliary tasks without a meaningful impact on the positioning pipeline were not considered. Only studies where ML was directly used to process UWB data, such as for LoS/NLoS classification, ToF/TDoA estimation, filtering, bias correction, or anchor selection, or where ML replaced classical fusion methods (e.g., neural networks instead of EKF or Unscented Kalman Filter (UKF)) were retained.

EC3. Studies validated exclusively through simulations were not included. This review focuses on works that include experiments carried out in real-world indoor environments.

EC4. Studies with experimental setups considered unrepresentative were excluded. This specifically refers to outdoor experiments, very small-scale areas (less than 10 m^2), or static calibration boxes that lack the multipath complexity and dynamic NLoS conditions inherent to real-world operation. As these setups do not reflect the signal propagation challenges that ML models aim to address, only works performed in realistic and sufficiently complex indoor scenarios were considered.

4.3. Search Strategy

The literature search was carried out in two major scientific databases, Scopus and WoS, on 15 May 2025. The search was limited to publications from 2020 to 2024. These databases were chosen because they offer broad coverage of engineering and computer science fields, including IPSs, and are considered reliable sources for high-quality research.

The search queries were designed to identify studies that combine UWB technology, indoor positioning, and the use of ML techniques. Different keywords, synonyms, and related expressions were used and connected through Boolean operators. Although the syntax was adapted to each database, the overall logic and structure of the queries remained consistent. The goal was to include as many relevant studies as possible and avoiding the omission of important contributions. The final dataset was then refined by applying the IC and EC defined earlier.

Scopus query:

```
TITLE-ABS-KEY("ultra-wideband" OR "ultrawideband" OR "ultra wide band" OR
"UWB")
AND TITLE-ABS-KEY("indoor" OR "IPS")
AND TITLE-ABS-KEY("loca*" OR "position*" OR "track*" OR "navig*" OR "CIR" OR
"NLOS" OR "TOA" OR "TDOA" OR "TWR")
AND TITLE-ABS-KEY("machine learning" OR "deep learning" OR "neural network*"
OR "CNN" OR "LSTM" OR "transformer*" OR "GAN" OR "autoencoder" OR "SVM" OR
"support vector machine" OR "random forest" OR "KNN" OR "k-nearest neighbor"
OR "decision tree" OR "XGBoost" OR "gradient boosting" OR "clustering" OR
"k-means" OR "Gaussian process*" OR "Bayesian network" OR "reinforcement
learning")
AND (LIMIT-TO (PUBYEAR,2024) OR LIMIT-TO (PUBYEAR,2023) OR LIMIT-TO
(PUBYEAR,2022) OR LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2020))
```

Web of Science query:

```
TS=("ultra-wideband" OR "ultrawideband" OR "ultra wide band" OR "UWB")
AND TS=("indoor" OR "IPS")
AND TS=("loca*" OR "position*" OR "track*" OR "navig*" OR "CIR" OR "NLOS" OR
"TOA" OR "TDOA" OR "TWR")
AND TS=("machine learning" OR "deep learning" OR "neural network*" OR "CNN"
OR "LSTM" OR "transformer*" OR "GAN" OR "autoencoder" OR "SVM" OR "support
vector machine" OR "random forest" OR "KNN" OR "k-nearest neighbor" OR
"decision tree" OR "XGBoost" OR "gradient boosting" OR "clustering" OR
"k-means" OR "Gaussian process*" OR "Bayesian network" OR "reinforcement
learning")
AND PY=(2020-2024)
```

The initial search retrieved 399 records from Scopus and 289 from WoS, resulting in a total of 688 entries. After removing 224 duplicates, 464 unique studies remained and were considered for the screening stage.

4.4. Study Selection Process

The study selection process was organized into four main stages—identification, screening, eligibility, and inclusion—following the general structure of the PRISMA (2020) framework. First, all records were collected from the selected databases and duplicates were removed. Then, the IC and EC were applied in two steps. The first step consisted of screening titles, abstracts, and keywords, while the second involved a full-text review to identify the final set of studies included in the analysis. The overall process is summarized in the PRISMA-inspired flow diagram shown below.

From the initial retrieval, 399 records were obtained from Scopus and 289 from WoS, giving a total of 688 documents. After removing 224 duplicates, 464 unique studies remained for the screening stage.

During the title and abstract screening, 165 records were excluded. Among these, 71 were not primary peer-reviewed publications (including 2 award summaries, 1 book, 38 conference reviews, 3 data papers, 13 theses, and 14 literature reviews). In addition, 25 studies were written in languages other than English, and 69 were unrelated to the use of UWB and ML in indoor positioning. As a result, 299 studies were selected for full-text examination. Of these, 10 reports could not be accessed due to institutional restrictions or the absence of publicly available full-text versions. Therefore, 289 studies advanced to the eligibility stage.

At this stage, 119 additional papers were excluded according to the predefined criteria. Specifically, 29 studies were removed because UWB was not a central component of the positioning system (EC 1) and 41 because ML was used only marginally without direct impact on the positioning pipeline (EC 2), 34 were based solely on simulations (EC 3), and 16 used experimental setups that were not representative of realistic indoor environments (EC 4). In the end, 169 studies were included in this comprehensive review.

The complete process is illustrated in the PRISMA (2020) flow diagram (Figure 2), which shows the number of records identified, screened, excluded with reasons, assessed for eligibility, and finally included in the review.

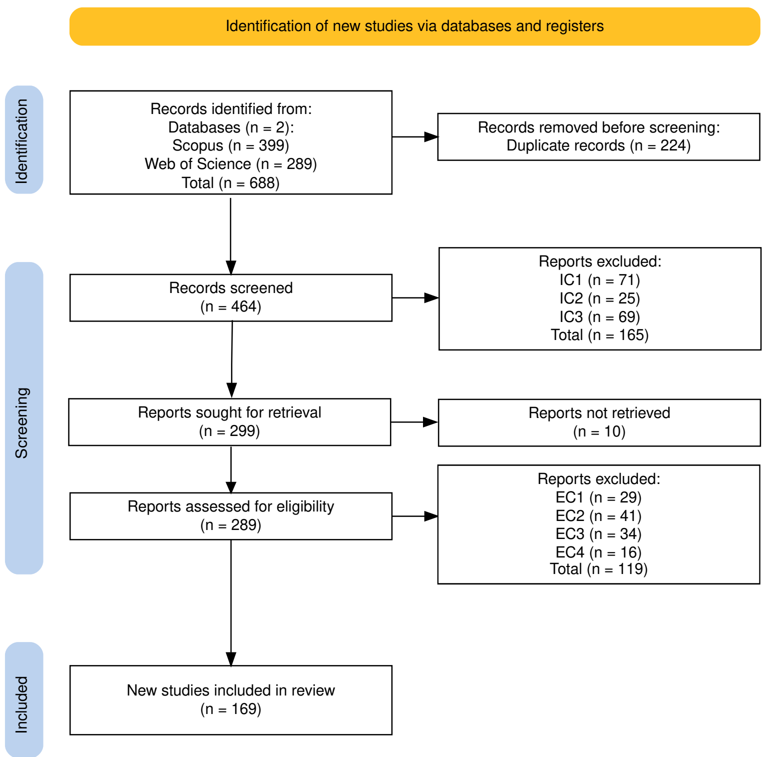

Figure 2. PRISMA 2020 flow diagram summarizing the study selection process.

4.5. Data Extraction and Analysis

After selecting the studies included in the review, the most relevant information from each paper was collected and organized for analysis. The main goal of this stage was to build a consistent dataset that could be used to classify and summarize the results in a clear and structured way.

For each study, several key characteristics considered essential for the analysis were recorded. These include the following:

- Bibliographic information, including the authors, year of publication, and the source where the study was published.
- The specific task or function within the UWB-based IPS where ML algorithms were applied, for example in channel condition classification, ranging error correction, or direct position estimation.
- ML algorithms used, specifying the type or family of models, including SVM, CNN, LSTMs, Autoencoders (AEs), and ensemble methods, among others.
- The evaluation metrics used to measure performance, for instance Root Mean Square Error (RMSE), Mean Absolute Error (MAE), classification accuracy, F1-score, or computational time.
- The experimental scenarios considered for validation, including environments such as laboratories, offices, industrial spaces, or in some cases, representative simulations.
- The datasets employed, indicating whether the study used public, private, or ad hoc data collections, and describing their role in improving comparability and reproducibility.
- The main reported results, especially those related to accuracy, robustness, error reduction, or improvements over baseline methods.

All the extracted information was organized into summary tables and coded according to the RQs defined in Section 4.1. The selected studies were also grouped by the main tasks within the UWB positioning pipeline, which made it possible to analyze how different types of ML algorithms contributed in each context.

The analysis of the collected data was conducted on two complementary levels:

1. A descriptive analysis, focused on quantifying several aspects such as the yearly distribution of publications, the frequency of use of each algorithm, the proportion of studies addressing each task, and the most common evaluation metrics.
2. A qualitative analysis, aimed at comparing the reported results, identifying performance trends across tasks and algorithms, and discussing the main challenges and recent directions in applying ML to UWB-based indoor positioning.

5. Results

The results are presented according to the five RQs outlined in Section 4.1.

5.1. Overview of Included Studies

A total of 169 primary studies were identified through the PRISMA selection process detailed in Section 4. Figure 2 presents the complete flow diagram of record identification and screening.

The temporal distribution of the included studies is summarized in Figure 3. The data indicate a marked upward trend in publication activity. After a brief dip in 2021, the yearly output increased from 20 to 54 papers by 2024, corresponding to a compound growth of nearly 170%.

In terms of publication type, the review comprises 104 journal articles (61.5%) and 65 conference papers (38.5%). While early contributions were evenly distributed, journal publications have become predominant, representing more than 70% of all studies in 2024.

This progression suggests a maturation of the research field, as initial exploratory findings presented at conferences have evolved into more comprehensive and rigorously validated journal articles.

This overview provides the contextual foundation for the analytical discussion of the research questions presented in the following sections.

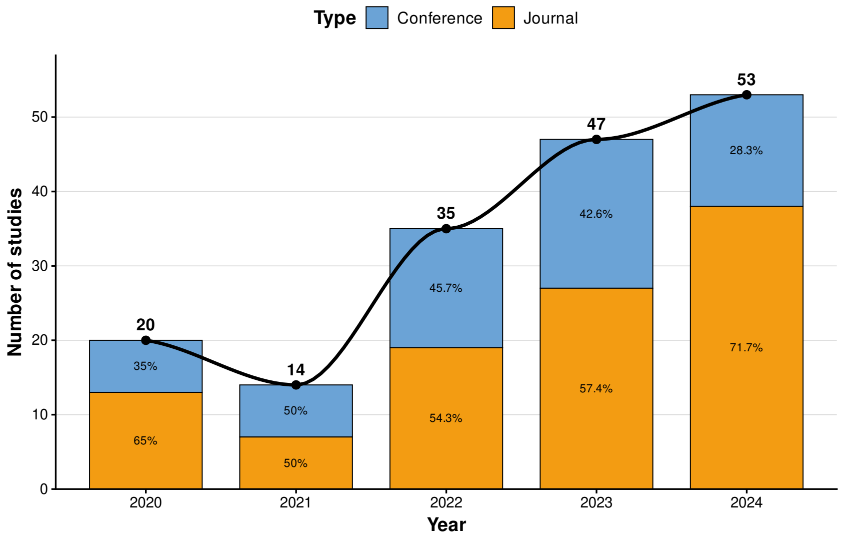

Figure 3. Annual distribution of the 169 included studies by publication type. The figure shows the accelerated growth of the field and the increasing predominance of journal articles in recent years, reflecting the topic's overall maturation.

5.2. RQ1. What Specific Tasks or Functions Within the Pipeline of UWB-Based Indoor Positioning Systems Are Addressed Through ML Algorithms?

Building on this general overview, the following sections examine in detail how ML contributes to specific functions within UWB-based positioning pipelines. To contextualize the role of ML, Figure 4 presents the classical pipeline used in UWB-based IPSs. This baseline architecture follows a deterministic flow that includes signal measurement (e.g., ToF or TDoA), range or angle estimation, geometric localization (e.g., multilateration or triangulation), and optional filtering through Kalman or particle filters. No learning-based adaptation is incorporated in this model, and all stages rely on fixed propagation assumptions, typically LoS conditions. In contrast, modern systems increasingly incorporate ML modules to enhance specific components of this pipeline, intervening at different stages, from early signal preprocessing to final coordinate estimation.

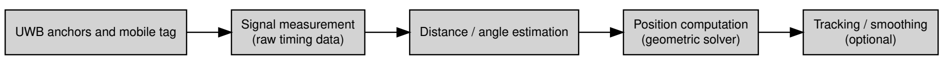

Figure 4. Baseline UWB positioning pipeline. Input dimensionality corresponds to scalar measurements $d \in \mathbb{R}$ (e.g., ToF or TDoA), while the output corresponds to estimated spatial coordinates $\mathbf{p} \in \mathbb{R}^2$ or $\mathbb{R}^3$ (representing 2D or 3D positions).

The application of ML within UWB-based IPSs is distributed across multiple functional stages of the positioning pipeline. Based on the analysis of 169 primary studies, a total of 199 instances were identified in which ML algorithms were employed to support or enhance specific components of the system. Multiple functional assignments may occur within a single study when different ML modules operate at separate stages of the pipeline.

Figure 5 presents the distribution of these applications across six functional stages. The most frequently targeted functional tasks are channel condition classification (83 occurrences) and ranging error mitigation (60), which are often combined to improve the reliability of distance measurements under multipath and NLoS conditions. Position estimation is addressed in 39 studies, covering both direct regression methods and fingerprinting-based localization. The high prevalence of classification and error mitigation tasks (together accounting for 143 of the 199 assignments) highlights that ML is currently perceived primarily as a robust compensator for physical layer impairments rather than a standalone replacement for geometric positioning.

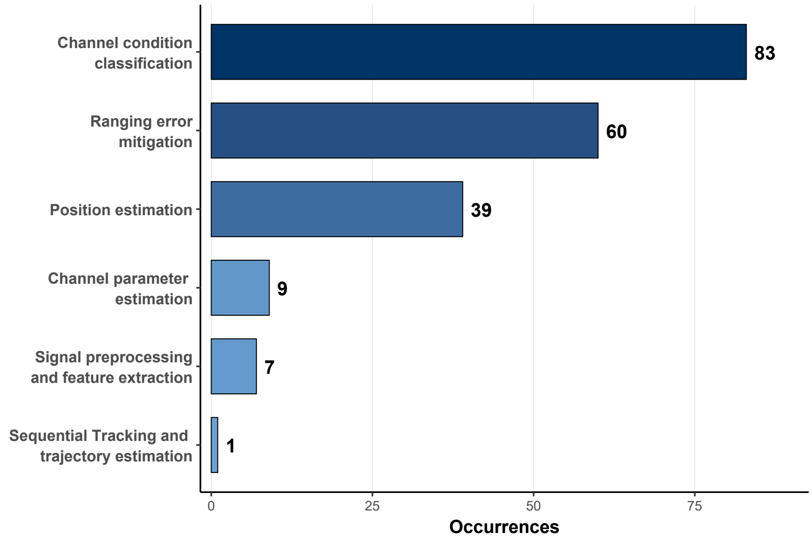

Figure 5. Distribution of the 199 functional assignments across the six stages of the UWB pipeline where ML techniques are applied. Multiple assignments can occur within a single study.

Less common applications include channel parameter estimation (9) and signal preprocessing and feature extraction (7). Only a single study addresses tracking and trajectory estimation, representing systems that explicitly model temporal evolution across consecutive UWB measurements.

Multimodal fusion approaches (e.g., UWB+vision or UWB+IMU) were included within the broader category of direct estimation, since the ML models in these systems operate directly on heterogeneous inputs, including UWB measurements, to infer position. In this taxonomy, fusion is therefore treated as an architectural variant of direct estimation rather than as a separate functional stage.

While Figure 5 quantifies how ML contributes to distinct functional tasks within the UWB positioning pipeline, these assignments often appear together within a single system. To capture how such tasks are integrated architecturally, the following analysis introduces a set of representative ML-enhanced pipelines (a–f). These pipelines correspond not to isolated tasks, but rather to common structural patterns in how ML modules are inserted within or replace specific components of the overall positioning pipeline. Figure 6 illustrates these representative pipelines.

To ensure a clear and consistent classification, pipelines are grouped according to the functional role and direct output of the ML module, rather than the overall system architecture. Specifically, category (a) includes systems where ML corrects raw UWB measurements (e.g., ranges or CIR) but leaves the position estimation to a traditional geometric solver. Category (b) comprises fusion models where ML integrates UWB data with additional sources (e.g., IMU, vision) to produce a joint position estimate. Category (c) is assigned to fingerprinting architectures that match UWB features to reference positions in a pre-constructed radio map. In contrast, (d) corresponds to models that learn a continuous mapping from raw UWB input to absolute coordinates, without predefined references or maps. Pipelines in (e) involve ML models that estimate intermediate propagation parameters (e.g., AoA, Time of Arrival (ToA)) rather than positions themselves. These parameters are subsequently used by geometric solvers for final localization. Finally, (f) covers models that learn motion dynamics or time dependencies from sequential UWB data to refine the trajectory across multiple measurements. This taxonomy emphasizes the functional role and output of the ML module, ensuring mutually exclusive classification.

(a) Channel assessment and ranging correction: This pipeline enhances traditional geometric localization through the insertion of ML modules for signal assessment and correction. The learning model operates on ranging and CIR data to classify the channel condition (LoS/NLoS) and to predict or mitigate the ranging bias. The corrected distances are then used by conventional solvers such as WLS or lateration to estimate the final position [8,11,28–96].
(b) UWB + IMU/vision sensor fusion: In this configuration, ML performs multisensor fusion, combining information from heterogeneous sources, typically UWB, inertial, or vision-based sensors, to obtain a unified position estimate. Bias correction may be incorporated as an optional intermediate step, while the final network output represents the fused position directly [7,97–105].
(c) UWB fingerprinting localization: This architecture replaces the geometric solver with a data-driven mapping between signal observations and a discrete set of reference locations. An offline radio map is first constructed from UWB features (e.g., CIR, RSS, ToF), and the ML model is trained to associate each fingerprint with its corresponding position. During online operation, the live input is matched to the most similar fingerprints and the final coordinates are obtained by classification or regression over this discrete set of reference points [9,106–108].
(d) Direct DL-based estimation: In contrast to fingerprinting, these pipelines learn a continuous mapping from raw or minimally processed inputs (e.g., CIR, ranges, images) directly to spatial coordinates or joint outputs such as position and NLoS class. No explicit radio map or geometric solver is maintained. Typical architectures include CNNs, LSTMss, and attention-based models that perform direct position regression from high-dimensional input data to (x, y, z) or to combined position/NLoS labels [109–136].
(e) Channel parameter estimation: In this configuration, ML modules infer intermediate propagation descriptors (e.g., AoA, TDoA, ToA, or amplitude) rather than predicting the final position. These learned parameters are then consumed by conventional geometric solvers, which perform multilateration or hybrid localization. Representative examples include [10,137–144].
(f) Sequential tracking and trajectory estimation: This pipeline focuses on modeling temporal evolution across consecutive UWB measurements. Here, ML learns motion patterns or state transitions, complementing instantaneous position estimates produced by traditional or learning-based localization modules. The tracking layer refines successive estimates into coherent trajectories [145].

Pipelines (a)–(d) represent the most frequently observed patterns, while (e) and (f) illustrate less common but functionally relevant stages. Rather than a rigid taxonomy, these configurations serve as analytical references for the specific ML algorithms discussed in the remainder of this section. It is important to note that the functional tasks analyzed next act as modular components (represented by the blue blocks in Figure 6) that can be integrated flexibly across different architectures; for instance, a channel classification module is typically found in pipeline (a), but can also serve as an auxiliary input in fusion frameworks like (b).

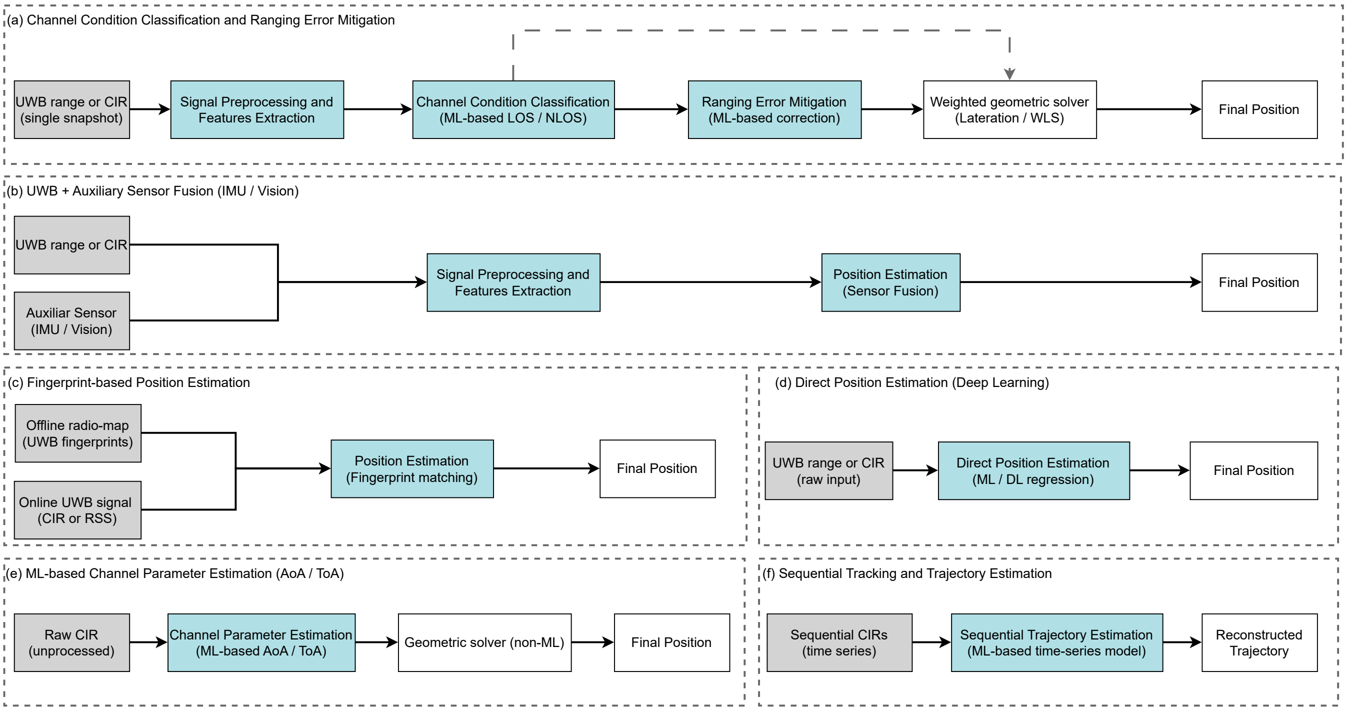

Figure 6. Representative ML-enhanced UWB positioning pipelines (**a**–**f**). Blue blocks indicate learning-based components, while gray and white blocks represent input sources and conventional modules, respectively. Input dimensionality varies: correction/fusion pipelines (**a**,**b**) process scalars $d \in \mathbb{R}$, whereas DL/fingerprinting models (**c**–**e**) process raw CIR vectors $\mathbf{h} \in \mathbb{R}^N$ (typically $64 \leq N \leq 1016$). Outputs range from discrete class labels $y \in \{0, 1, \ldots, K\}$ (for binary or multiclass tasks) to position estimates $\mathbf{p} \in \mathbb{R}^2$ or $\mathbb{R}^3$.

5.2.1. Signal Preprocessing and Feature Extraction

Signal preprocessing constitutes the initial stage of the UWB positioning pipeline. It focuses on preparing raw measurements, such as the CIR or range estimates, before subsequent processing steps like classification, ranging correction, or position estimation. The objective is to improve data reliability by suppressing noise, reducing variability, and enhancing measurement consistency under NLoS or multipath conditions.

Waveform denoising and signal stabilization: Several contributions implement techniques to suppress transient distortions in the CIR, aiming to produce cleaner and more consistent waveforms for subsequent processing. This includes methods that reduce high-frequency components and mitigate the effects of multipath interference, especially in highly reflective or cluttered indoor environments [28,146].

Filtering of outliers and irregular samples: In some systems, signal filtering is performed through clustering-based mechanisms that group similar observations and discard inconsistent measurements. This step enhances data quality before position estimation or trajectory inference, particularly in tracking scenarios with multiple targets or noisy reflections [29,147,148].

Data augmentation and domain expansion: A subset of studies generates synthetic data to improve dataset diversity and coverage. This includes the creation of additional samples for underrepresented propagation conditions, or the simulation of target-domain scenarios when real data are scarce. Augmented datasets are later used in channel classification, ranging correction, or localization modules [48,149].

In total, seven studies implement signal preprocessing or augmentation techniques within the UWB positioning pipeline. These mechanisms contribute to improve the reliability of downstream modules by producing structured, filtered, or enriched input data.

5.2.2. Channel Condition Classification

This functional category includes systems that infer the propagation condition of UWB links, identifying whether a signal is affected by LoS obstruction, multipath interference, or other types of channel degradation. Within the positioning pipeline, this stage typically follows signal acquisition or preprocessing and provides channel-state information that supports ranging error mitigation, measurement selection, or sensor fusion. A total of 83 studies implement classification mechanisms at this stage.

Binary Classification of Channel Conditions: The majority of the contributions (53) implement binary classification schemes, which distinguish between LoS and NLoS conditions. In these systems, the classification output serves as a filtering mechanism to identify potentially biased measurements. Common uses include triggering NLoS corrections, assigning measurement weights, or excluding unreliable ranges from geometric localization. In several cases, binary classification is combined with probability estimation, allowing subsequent modules to integrate confidence scores into weighting functions or filtering processes. This enables a more flexible adaptation of positioning algorithms based on the estimated channel reliability [7,8,30–32,35,37–43,46,49,53,54,59–62,64,68,81,88,96–98,149–172].

Multiclass and Context-Aware Classification: In contrast to binary schemes, a subset of systems (30) implement multiclass or context-aware classification. These systems differentiate between various NLoS conditions (e.g., soft-NLoS, hard-NLoS), or classify specific environmental obstructions such as walls, human bodies, glass, or metal. Some works also use classification to identify subregions of the environment, device placement positions, or different signal degradation contexts. This refined classification is used to support advanced correction strategies, spatial segmentation, or dynamic adaptation of positioning algorithms in complex indoor scenarios. This approach is particularly relevant in applications requiring fine-grained environmental awareness or robustness under heterogeneous propagation conditions. Representative studies include [33,36,44,45,47,48,51,52,55,58,63,79,84,88,90,96,107,108,117,149,173–181].

5.2.3. Ranging Error Mitigation

This functional task refers to the use of learning-based mechanisms to reduce or compensate for distortions in the estimated distances between UWB anchors and tags. These distortions, typically caused by multipath propagation, NLoS conditions, body shadowing, signal obstruction, or tag orientation, introduce significant bias in time-based ranging methods such as ToF, TDoA, or DS-TWR. A total of sixty studies were classified under this task.

Direct Bias Correction: These studies correct deterministic range errors caused by known factors such as static bias, hardware imperfections, or fixed environmental effects. The models estimate corrected distances directly from the raw measurements before geometric localization. This group includes [6,28,39,44,57,67,69,72,73,75–77,86,88,92,94,111,127,182].

Context-Aware Mitigation: In these systems, bias correction adapts dynamically to environmental or channel conditions. Contextual variables such as CIR features, signal strength, or channel classification are used to estimate the severity of NLoS or multipath effects. Representative works include [46,63,64,66,70,71,74,79,82,84,85,89,90,93,95,108,127,140,142,167].

Fusion-Integrated Correction: This category involves systems where the range correction is embedded into sensor fusion, filtering, or pose estimation processes. Instead of correcting distances in isolation, these approaches jointly optimize with modules such as EKF, factor graphs, or trajectory models. Studies in this group include [34,36,65,75,83,100–104,107,183].

5.2.4. Channel Parameter Estimation

This functional stage refers to the extraction of physical propagation parameters from UWB signals prior to coordinate estimation. These descriptors provide intermediate information about the geometry and quality of the radio channel, enabling downstream tasks such as hybrid localization, geometric multilateration, or multipath exploitation.

A total of nine studies were classified in this category. Their objective is not to estimate the final position of the target, but to infer parameters such as AoA, PDoA, ToA, TDoA, or signal amplitude, which are later consumed by non-ML modules for position computation.

Angle-based Estimation (AoA, PDoA): Several contributions target the estimation of directional parameters that characterize the angle at which the signal arrives at the receiver. These include the prediction of AoA from CIR amplitude and phase profiles using DL modules [137,138], and the modeling of PDoA distributions to resolve phase ambiguity prior to tracking [143].

Timing-based Estimation (ToA, TDoA): Another set of works focuses on the estimation of signal propagation times, such as ToA or TDoA. These parameters replace traditional estimators (e.g., peak detectors or Leading-Edge Detection (LDE)), a classical method for identifying the first significant path arrival in UWB signals, with learning-based inference from the CIR [10,141,144].

Joint Estimation of Multiple Parameters: Some approaches infer several channel descriptors simultaneously, enabling a more complete geometric modeling of multipath propagation. These include combinations of distance, angle, and time information [140,142].

Amplitude-based Characterization: One study predicts the amplitude and Signal-to-Interference-plus-Noise Ratio (SINR) of dominant multipath components, producing a fine-grained power profile of the UWB channel for later use in localization algorithms [139].

In summary, this stage represents the process of extracting geometric and physical channel features from raw UWB data, which are subsequently leveraged for position estimation or correction tasks in other pipeline stages.

5.2.5. Position Estimation

This functional category represents the final stage of the UWB-based positioning pipeline, where spatial coordinates are obtained or refined based on previously processed signal measurements. A total of 39 studies were assigned to this category.

Direct position estimation: Most systems compute coordinates directly from UWB-derived inputs, such as distances, CIR features, or ToF values, bypassing explicit multilateration. These models learn non-linear mappings from signal features to final (x, y, z) coordinates through direct position regression. Some methods rely solely on static input [33,105,109–111,115,119,123–125,130–132,135,136,184], while others incorporate temporal or spatial–temporal dependencies to improve prediction in dynamic scenarios, including motion-aware or multi-tag setups [99,112,113,120,122,129].

Position calibration and correction: A subset of studies applies correction over previously estimated positions, refining (x, y) or (x, y, z) outputs to reduce residual error caused by anchor misplacement, NLoS effects, or model limitations. This includes both classical lateration systems and commercial IPS platforms, with correction strategies applied via regression over initial coordinates [114,116,126,127,133,185].

Fingerprinting-based localization: Other contributions use fingerprinting techniques, training models to associate input features (e.g., CIR, RSS, ToF) with previously labeled reference points. These systems infer position by regression or similarity matching against stored fingerprints. This group includes both UWB-only approaches [9,106,128,134,141] and multi-technology systems combining additional sensors such as Wi-Fi or magnetometers [118,186,187].

In all these systems, the ML component is applied directly to infer or adjust spatial coordinates, completing the positioning pipeline with a final coordinate output.

5.2.6. Sequential Tracking and Trajectory Estimation

While not present in most conventional UWB positioning pipelines, this additional stage captures the temporal dynamics of user motion across consecutive signal measurements.

Only one study was identified under this functional task [145]. It proposed a device-free indoor tracking method that infers user movement by analyzing variations in the CIR over time. The system classifies movement patterns, combining position and direction, across a predefined set of trajectories. These sequences are then refined using a path-finding algorithm that accounts for environmental structure and motion continuity, yielding complete trajectory reconstructions.

Importantly, this pipeline operates without wearable tags, relying solely on UWB signal reflections. It represents a distinct approach to UWB-based positioning, focused on dynamic tracking rather than instantaneous location estimation.

Overall, these four pipelines summarize the principal ways in which ML has been integrated into UWB-based positioning, either as an auxiliary component for signal correction or as a complete data-driven estimator of position. This classification provides the structural basis for the analysis of algorithmic choices and performance outcomes in RQ2 and RQ3.

5.3. RQ2. Which ML Algorithms Are Most Commonly Applied to These Tasks, and What Motivations or Advantages Are Reported in the Literature to Justify Their Use?

Based on the functional taxonomy established in Section 5.2, the analysis in RQ2 focuses on the specific ML models employed within each stage of the UWB positioning pipeline. A total of 199 assignments were identified across six functional categories, including signal preprocessing, channel classification, ranging error mitigation, channel parameter estimation, position estimation, and sequential tracking.

For each category, the types of ML models used, their frequency of occurrence, and representative architectural patterns are reported. The results are presented in a stage-wise manner, with one subsection per functional category. In each case, a summary table enumerates the distinct models applied, along with study references.

5.3.1. Technical Motivation and Limitations of ML Models for UWB Positioning

The prominence of specific ML architectures in the reviewed literature is grounded in their theoretical alignment with the physical properties of UWB signals. Before analyzing their application in specific pipeline stages, this subsection outlines why these models are particularly effective for processing CIR data and handling propagation challenges.

The selection of ML models in UWB-based IPS is fundamentally driven by the physical characteristics of the radio channel and the structure of the CIR. The CIR acts as a location-dependent fingerprint of the environment, where LoS conditions concentrate energy in the first path, while NLoS scenarios introduce delayed multipath components and non-linear ranging biases. Traditional analytical models struggle to capture these effects, which has motivated the widespread adoption of data-driven approaches in the literature.

CNNs are particularly effective for CIR-based processing due to their inductive bias toward locality and translation invariance. Multipath effects manifest as local peak patterns and energy distributions within the CIR that may shift in time due to distance variations or clock jitter. CNNs can detect such patterns independently of their absolute position, enabling robust extraction of multipath signatures directly from raw CIR data without handcrafted feature engineering [31,162]. Furthermore, recent approaches extend this principle by transforming 1D CIR signals into 2D time–frequency images (e.g., using Gramian Angular Fields), allowing the exploitation of vision-based architectures [79].

Temporal models such as LSTMs, Gated Recurrent Unit (GRU), and Temporal Convolutional Network (TCN) exploit the temporal coherence of both user motion and channel conditions. In realistic deployments, NLoS states and ranging errors exhibit strong temporal persistence, which sequential models can leverage to smooth position estimates, compensate for intermittent signal blockages, and improve tracking robustness compared to snapshot-based methods [113,120].

Classical ML models, including SVMs and RF, remain relevant when operating on low-dimensional UWB features (e.g., ToF, RSS, First-Path (FP) energy). Their margin maximization, robustness to small datasets, and low computational complexity explain their historical success in LoS/NLoS classification and bias mitigation tasks, particularly in embedded scenarios where DL deployment is constrained [44,52].

Despite their effectiveness, the reviewed studies consistently report significant limitations for ML-based UWB positioning methods. In particular, deep models often exhibit poor generalization across environments due to non-stationary CIR statistics and hardware-dependent signal distributions. Performance degradation is commonly observed when models trained in one environment or device configuration are deployed in another, as documented by Fontaine et al. [96] and Hua et al. [166]. Furthermore, several studies note that high computational costs hinder scalability on resource-constrained devices, frequently motivating the adoption of domain adaptation strategies or lightweight model designs.

5.3.2. Signal Preprocessing and Feature Extraction

In this initial stage of the UWB positioning pipeline, ML techniques are employed to clean, organize, or enrich raw measurements prior to downstream processing. Seven studies employed such models to support signal denoising, clustering-based filtering, or synthetic data generation, aiming to improve robustness under multipath and NLoS conditions.

Clustering-based methods: Unsupervised clustering, particularly using density-based algorithms, was applied to isolate reliable measurements and remove outliers from CIR data. These approaches were primarily integrated in passive tracking or radar-inspired UWB systems, where noisy reflections or overlapping trajectories required filtering before range or position estimation [29,147,148].

AE-based and transformer-based denoising: Deep neural architectures were explored to suppress signal noise and enhance temporal consistency in CIR measurements. Variational and denoising AEs were used for waveform reconstruction and latent feature extraction from raw UWB signals [28], whereas transformer-based networks incorporated attention mechanisms to emphasize relevant temporal components under varying propagation conditions [146].

Generative models for data augmentation: Generative Adversarial Networks (GANs) were employed to expand training datasets by synthesizing realistic CIR samples, particularly in scenarios with class imbalance or limited measurement diversity. These models were often coupled with Transfer Learning (TL) or feature-based classification pipelines to enhance downstream channel-condition identification [48,149].

As summarized in Table 3, clustering-based and AE-based approaches remain the most frequently adopted in this functional block, while generative and transformer-based models have recently emerged to improve data diversity and temporal feature representation.

Table 3. ML models applied to Signal Preprocessing and Feature Extraction. Each occurrence corresponds to a distinct model used within this functional category.

ML Model	Occurrences	References
Clustering-Based Methods	3	[29,147,148]
Autoencoder	2	[28,48]
GAN (Generative Adversarial Network)	2	[48,149]
Transformer-Based Model	1	[146]

Note: Bar length and color intensity indicate the frequency of model usage.

5.3.3. Channel Condition Classification

This functional stage encompasses 83 studies that employ ML models to distinguish LoS from NLoS conditions, or to identify specific propagation contexts such as multipath interference, dynamic obstructions, or environmental categories. As summarized in Table 4, a broad variety of learning paradigms has been explored, with CNNs being by far the most prevalent approach.

Table 4. ML models applied to Channel Condition Classification. Each occurrence corresponds to a distinct model used within this functional category.

ML Model	Occurrences	References
Convolutional Neural Network	35	[30,31,37,38,43,45,47,49,50,53,55,56,59,60,67,79,85,90,96,150,152,154,155,157,159,160,162,165,169,172,174,177,178,180,188]
Support Vector Machine	21	[7,32,34,42–44,46,48,51,52,61,81,84,98,149,156,164,170,172,173,176]
Random Forest	9	[35,44,52,108,151,153,170,172,176]
Long Short-Term Memory Network	10	[47,58,67,85,90,150,156,172,180,188]
Deep Neural Network	9	[8,62,68,96,117,158,161,166,175]
k-Nearest Neighbors	7	[44,61,107,152,164,170,172]
Decision Tree	5	[51,62,156,176,179]
Ensemble Methods	5	[39,44,63,88,172]
Multilayer Perceptron	6	[50,52,61,81,164,177]
Naïve Bayes	4	[40,41,44,168]
XGBoost	4	[64,163,164,176]
Recurrent Neural Network	4	[49,55,171,178]
Variational Autoencoder	3	[33,36,171]
Transformer-Based Models	3	[54,167,181]
Gaussian Mixture Model	2	[97,151]
Clustering-Based Methods	1	[156]
Other Methods	1	[170]

Note: Bar length and color intensity indicate the frequency of model usage.

Convolutional architectures and variants: CNN-based models dominate this functional block, appearing in 35 studies. Standard feedforward and convolutional structures are widely used for binary LoS/NLoS discrimination [8,96], while deeper variants such as Residual Network (ResNet) [31,154], Fully Convolutional Network (FCN) [37,162], and TCN [56,160] enable hierarchical or temporal feature extraction. Attention-enhanced CNNs further refine signal representations by focusing on dominant multipath components [55,180]. Several architectures combine convolutional blocks with recurrent units such as LSTMs or Bidirectional Long Short-Term Memory (BiLSTM) for sequential modeling [51,85], while others integrate specialized designs like Hybrid Quantum Convolutional Neural Network (HQCNN) for nonlinear feature embedding [41,59].

SVMs and ensemble classifiers: SVMs constitute the second most frequent algorithm (21 occurrences), applied both as standalone classifiers [42,173] and as components of hybrid or comparative frameworks. In several studies, SVMs are combined with data preprocessing modules such as AEs or GANs [48,149], or are evaluated alongside tree-based ensembles including RF and gradient-boosting models such as Extreme Gradient Boosting (XGBoost) [44,170,176]. These combinations aim to improve generalization under diverse propagation scenarios and address class imbalance issues.

Recurrent and attention-based networks: Temporal learning mechanisms are also represented by recurrent neural architectures, particularly LSTMs units, which model sequential dependencies in the CIR. They are frequently integrated with convolutional encoders [58,90,150] or extended via GRU and attention-based modules [67,180]. Transformer-based classifiers are less common but introduce novel attention-driven strategies such as Domain Adaptation (DA) [181] and Bidirectional Encoder Representations from Transformers (BERT)-style encoding for NLoS pattern recognition [167].

Alternative and emerging models: Other learning strategies include Multilayer Perceptrons (MLPs) [50,177], decision-tree variants [179], Gaussian Mixture Model (GMM) [151], and boosting methods such as XGBoost and Light Gradient Boosting Machine (LightGBM) [64,163]. AEs and Variational Autoencoders (VAEs) are occasionally adopted for feature learning and anomaly detection [33,36]. More specialized formulations include Variational Recurrent Neural Network (VRNN) [171] and HQCNN [41]. Clustering-based classifiers and probabilistic models such as Naïve Bayes appear as auxiliary components within hybrid or comparative pipelines [156,168].

Overall, this stage exhibits the highest architectural diversity within the UWB learning pipeline. Convolutional and recurrent architectures remain dominant for feature-rich signal modeling, while ensemble and boosting techniques provide interpretable and computationally efficient alternatives for deployment on resource-limited hardware.

5.3.4. Ranging Error Mitigation

This functional stage encompasses 60 studies that employ ML models to mitigate or compensate ranging errors in UWB systems. These errors, typically caused by NLoS propagation, multipath interference, tag orientation, or device heterogeneity, introduce systematic biases that degrade distance and position accuracy. As summarized in Table 5, a diverse set of models has been proposed for bias estimation, including deep neural networks, probabilistic formulations, and clustering-based corrections.

Table 5. ML models applied to Ranging Error Mitigation. Each occurrence corresponds to a distinct model used within this functional category.

ML Model	Occurrences	References
Convolutional Neural Network	15	[6,28,46,67,71,74,79,82,85,88,93,96,127,182,189]
Long Short-Term Memory Network	12	[6,58,67,69,83,85,86,92,93,103,104,127]
Deep Neural Network	10	[6,11,63,87,91,96,102,111,144,183]
Autoencoder	6	[28,36,83,103,140,142]
Gaussian Mixture Model	5	[70,78,89,95,100]
SVM/SVR	4	[34,73,81,84]
k-Nearest Neighbors	3	[76,107,190]
Clustering-Based Methods	3	[65,66,101]
Random Forest	3	[44,80,108]
Ensemble Methods	3	[44,75,88]
Gaussian Models	2	[67,94]
Multilayer Perceptron	2	[81,90]
Transformer-Based Models	2	[127,167]
Recurrent Neural Network	2	[86,93]
Decision Tree	1	[39]
XGBoost	1	[11]
Other Models	5	[57,64,72,77,140]

Note: Bar length and color intensity indicate the frequency of model usage.

Convolutional and recurrent neural networks: CNNs represent the most widely adopted model at this stage, appearing in 14 studies. Many works apply CNNs directly to CIR data for bias regression, using compact implementations such as Residual Enhancement Multiscale Network (REMNet) [71,74] or deeper hybrid designs incorporating ResNet modules [79]. Temporal variants couple CNN encoders with LSTMs units to model the time-varying dynamics of ranging bias [85,127], and some integrate additional recurrent layers such as GRU or Transformer-based attention modules [93]. LSTMs architectures alone, reported in 12 studies, learn sequential error dependencies or predict time-evolving NLoS biases directly from CIR or ToF sequences [6,69,92].

AEs and generative models: AE-based models are employed in this stage to directly estimate or compensate the systematic bias present in UWB range measurements. Rather than acting solely as denoising modules, these networks learn a mapping between distorted and bias-free distances. VAEs are used both as standalone regressors [36,142] and within hybrid frameworks combining recurrent components such as LSTMs units [103]. By learning latent generative representations of LoS and NLoS propagation effects, these models enable continuous bias correction and improve robustness across heterogeneous environments.

Tree-based and ensemble regressors: Tree ensembles such as RFs, Gradient Boosted Regression Trees (GBRT), and XGBoost are also common, used to regress distance bias from engineered features derived from the CIR or ToF [44,75,77]. In some cases, these models are integrated into probabilistic localization pipelines or coupled with EKF to enhance tracking robustness under NLoS conditions [64,80].

Support vector and shallow networks: Support Vector Regression (SVR) and similar shallow architectures are used to estimate bias in small-scale or hybrid systems [73,84]. Lightweight feedforward networks and MLPs also serve as efficient regressors for bias estimation in resource-constrained platforms [81,111]. In some implementations, MLP modules are conditioned on channel classification results to refine range corrections [90].

Probabilistic and clustering-based approaches: Several studies rely on GMMs to model probabilistic distributions of ranging errors, often associated with body shadowing or ToA variance [70,78]. Bayesian extensions such as Variational Bayesian Gaussian Mixture Model (VBGMM) [100], as well as clustering schemes including Fuzzy C-Means (FCM), k-means, and Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA) [65,66], are used to separate LoS/NLoS measurements and substitute or reweight biased ranges. These models often act as preprocessing or filtering layers within larger localization frameworks.

Analytical and hybrid regression models: A smaller group of studies explores analytical models such as Gray Model (GM) and Gaussian Process Regression (GPR) for temporal bias prediction under limited training data [64,94]. These methods illustrate the incorporation of semi-empirical and hybrid regression strategies into ML-assisted ranging pipelines, providing interpretable alternatives where data availability or computational resources are constrained.

Overall, this functional block reveals a clear trend toward combining data-driven regression models with statistical or filtering techniques to achieve robust bias correction. Deep architectures such as CNNs, LSTMss, and VAEs dominate in high-data scenarios, while ensemble and probabilistic methods remain attractive for real-time and embedded UWB localization systems.

5.3.5. Channel Parameter Estimation

This functional stage encompasses nine studies that address the estimation of physical-layer parameters derived from the UWB channel, such as ToF, TDoA, AoA, and PDoA. These parameters serve as essential inputs for subsequent positioning and tracking modules. As summarized in Table 6, recent works combine deep neural architectures and probabilistic modeling to improve parameter estimation under multipath and single-anchor conditions.

Table 6. ML models applied to Channel Parameter Estimation. Each occurrence corresponds to a distinct model used within this functional category.

ML Model	Occurrences	References
Convolutional Neural Network	3	[10,137,138]
Autoencoder	2	[140,142]
Gaussian Mixture Model	1	[143]
Gaussian Process Regression	1	[139]
Multilayer Perceptron	1	[138]
Other Neural Network Models	2	[141,144]

Note: Bar length and color intensity indicate the frequency of model usage.

Convolutional architectures: CNNs are the most common approach in this stage (3), used to estimate propagation parameters directly from the CIR. For example, Wang et al. [137] proposed a residual CNN with nine layers for joint amplitude and phase-of-arrival estimation, while [10] applied a deep residual CNN to predict ToF of reflected paths. A lightweight SE-CNN combined with a three-layer MLP was used for multi-path component selection and AoA regression [138].

AE and generative models: VAEs are explored to jointly infer distance-related quantities, such as first-path distance, ToF, or TDoA, and latent propagation parameters. The VAE-based architectures in [140,142] learn compact generative representations of multipath profiles, enabling robust recovery of physical parameters under NLoS and reflective conditions.

Dense and hybrid neural networks: Artificial Neural Networks (ANNs) and fully connected designs are adopted as lightweight alternatives for regression of ToA and TDoA values [141,144]. These compact models are suitable for embedded or single-anchor systems where inference latency and computational cost are critical constraints. Similarly, the MLP submodule in [138] maps CNN-extracted features into precise AoA estimates.

Probabilistic and analytical models: Probabilistic models are used to capture the uncertainty inherent in multipath-rich channels. GMM describe the wrapped ambiguity of phase-of-arrival measurements [143], while GPR provides a non-parametric framework for predicting amplitude and SINR distributions [139]. These analytical methods remain attractive when data availability is limited or interpretability is prioritized over network complexity.

Overall, this stage highlights the convergence between DL and probabilistic inference for fine-grained recovery of UWB channel parameters.CNNs and VAEs dominate the learning-based estimation of ToF and AoA, whereas GMM and GPR models provide interpretable alternatives for uncertainty quantification and low-data scenarios.

5.3.6. Position Estimation

This functional stage includes 39 studies that use ML to estimate the final coordinates of the target tag. These models operate either through direct regression from raw UWB signal features, or as calibration components that refine initial position estimates. Table 7 presents the main ML models identified for this task.

Convolutional and deep neural networks: CNNs are the most common models for position estimation (13), often used to process CIR features for fingerprinting-based localization [9,127]. Many studies adopt direct position estimation CNN architectures that directly map UWB signal inputs to 2D or 3D coordinates, or integrate convolutional layers with additional modules like GRU or Transformer encoders for geometric embedding and temporal context modeling [112,126]. Fully connected Deep Neural Networks (DNNs) also appear frequently, either as standalone regressors [105,132], or as components in hybrid pipelines with TL or sensor fusion [118,185].

Recurrent models and hybrid architectures: LSTMs-based models (7) are used for sequential modeling of distance or CIR inputs, often improving robustness under NLoS or signal loss conditions [99,113]. Hybrid architectures that combine LSTMs with Kalman filters, CNNs, or GRU blocks are also reported, enabling resilient localization under dynamic conditions [127,131]. Other recurrent models include encoder–decoder LSTMs predictors [122], and GRU-based sensor fusion systems [105].

Transformers and graph-based models: Transformer-based models are increasingly adopted for CIR-based fingerprinting, due to their ability to capture long-range dependencies and generalize across environments [112,128]. Graph-based models, including Graph Neural Networks (GNNs), Graph Convolutional Networks (GCNs), and Graph Attention Networks (GATs), are used to encode spatial relationships between anchors and enhance positioning accuracy under multipath and NLoS conditions [129,130,135].

Shallow and classical models: While DL dominates this stage, shallow models such as MLPs [187], RFs [186], SVMs [110], and ensemble regressors like XGBoost [119] remain in use, particularly in resource-constrained or embedded applications. Some studies apply clustering or k-Nearest Neighbors (kNN) regression for fingerprint matching or anchor selection under hybrid schemes [115,121,134].

Table 7. ML models applied to Position Estimation. Each occurrence corresponds to a distinct model used within this functional category.

ML Model	Occurrences	References
Deep Neural Network	14	[33,105,106,108,109,111,114,117,118,123,132,136,184,185]
Convolutional Neural Network	7	[9,73,116,120,125–127]
Long Short-Term Memory Network	7	[99,106,113,120,122,127,131]
Transformer-Based Models	3	[112,127,128]
k-Nearest Neighbors	3	[121,134,186]
Multilayer Perceptron	3	[124,133,187]
Support Vector Machine	1	[110]
Clustering-Based Methods	1	[115]
XGBoost	1	[119]
Gaussian Mixture Model	1	[184]
Random Forest	1	[186]
Recurrent Neural Network	1	[112]
Other Neural Networks	6	[108,129,130,135,141,186]

Note: Bar length and color intensity indicate the frequency of model usage.

Position estimation tasks exhibit the most diverse set of models among all functional stages. As shown in Table 7, CNNs and LSTMss are the most common, but several advanced architectures are emerging, such as Transformers, GNNs, and metaheuristic-optimized networks. While many approaches focus on improving regression accuracy, others emphasize generalization, robustness, or online adaptability.

5.3.7. Sequential Tracking and Trajectory Estimation

Only one study was identified within this functional stage. As shown in Table 8, a CNN was applied to analyze temporal variations of the CIR and to classify movement patterns from amplitude and phase information [145]. The resulting classifications were subsequently processed through a path-finding algorithm to reconstruct complete movement trajectories based on the spatial layout constraints.

Table 8. ML models applied to Sequential Tracking and Trajectory Estimation. Each occurrence corresponds to a distinct model used within this functional category.

ML Model	Occurrences	References
Convolutional Neural Network	1	[145]

Note: Bar length and color intensity indicate the frequency of model usage.

5.3.8. Number of Layers in CNN and DNN Architectures

Tables 9 and 10 summarize the DL architectures employed for UWB-based indoor localization between 2020 and 2024. Overall, CNNs represent the dominant choice across studies, reflecting their ability to extract spatial and temporal patterns from raw CIR data. By contrast, DNNs and Feedforward/Backpropagation Networks are often adopted for lighter tasks such as feature-based classification, ranging error correction, or data fusion. For the sake of brevity in the Architecture Summary column, common layer abbreviations are utilized: Convolutional (Conv), Fully Connected (FC) (Dense), Batch Normalization (BN), and Maximum Pooling (MaxPool) layers.

Table 9. Summary of CNN architectures for ML-based UWB indoor localization.

DL Model	Architecture Summary	Depth	Reference
AE-CNN	AE encoder–decoder + CNN head.	5	[28]
CNN	Conv + MaxPool + FC + Softmax.	4	[30]
CNN-LSTM	2 Conv + Pool + FC + LSTM + Softmax.	5	[150]
CNN	4 Conv1D + Pool + 2 FC + Softmax.	7	[50]
CNN	Conv + MaxPool + FC.	6	[53]
CNN (ResNet/FCN)	ResNet encoder + FCN variant.	11	[31]
CNN	2 Conv2D + 2 MaxPool + 3 FC.	7	[73]
ResNet (1D CNN)	1 Conv1D + 6 ResBlocks + 2 FC.	9	[137]
REMNet	1D Conv + 3 Residual Modules + FC.	7	[71]
CNN	4 Conv + 4 FC.	8	[189]
CNN	5 Conv + 3 Pool + 2 FC.	10	[43]
CNN	3 Conv + MaxPool + 2 FC.	6	[145]
CNN + FC	3 Conv + Pool + 4 FC.	8	[116]
CNN + LSTM	4 Conv3D + FC + LSTM.	9	[120]
PLN (CNN + MLP)	CNN + MLP + Fusion FC.	8	[138]
CNN (Residual)	Conv + BN + ReLU + Pool + FC.	8	[56]
REMNet (1D-CNN)	3 Residual Modules + FC.	6	[74]
TCN + Attention	Dilated Conv + Residual + Attention + FC.	8	[10]
ININN (CNN + GRU + SE)	2 Conv + BN + Pool + GRU + SE-Att.	12	[178]
CNN (1D)	5 Conv + Pool + FC.	8	[45]
Wavelet-CNN	5 Conv + Pool + FC.	8	[174]
Parallel GRU + CNN	GRU + 4 Conv + Pool + FC.	10	[55]
Multi-stream CNN	3 parallel CNN streams + FC.	21	[49]
DLRC (CNN + FC)	5 Conv + BN + FC.	7	[126]
CNN (anchor-subset)	Multi-CNN (Conv + Pool + FC).	7	[9]
C-T-CNN-SVM	3 Conv + Pool + 2 FC.	5	[46]
ECA-ResNet	Residual CNN + Attention + Pool + FC.	12	[82]
MPCM (CNN + LSTM + Transf.)	3 Conv + LSTM + Transformer + FC.	9	[127]
MPCM + ADM	MPCM + LSTM + MLP.	12	[127]
CNN + ResNet18 (SE)	Dual CNN + ResNet18 + Fusion FC.	20	[154]
MIPL (CNN + ResNet18 + RSS)	CNN + ResNet + SE + FC.	22	[79]
WGCNN	2 Conv + 2 Pool + FC.	6	[38]
CNN + LSTM	4 Conv + LSTM + FC.	7	[47]
Hybrid Quantum CNN	QCNN (Conv + Pool + FC).	6	[59]
Hybrid Quantum CNN (8q)	QCNN (2 Conv + 2 Pool + FC).	6	[60]
IDBO-CNN	3 Conv + 3 Pool + 2 FC.	8	[155]
ST-CNN + TL	CNN (Conv + Pool + FC).	8	[157]
CNN-BiLSTM-Attention	2 Conv + Pool + BiLSTM + Att. + FC.	8	[180]
EMD-WD-CNN	Conv + Pool + FC.	6	[169]
CNN-LSTM	Conv + Pool + LSTM + FC.	7	[85]
CNN-LSTM + WLS	CNN-LSTM + WLS fusion.	7	[85]
CNN + LightGBM	4 Conv + Pool + FC.	6	[88]
TL-CNN (raw CIR)	3 Conv1D + Pool + FC.	6	[96]
Denoising CNN	Conv1D + Pool + GlobalAvgPool + FC.	4	[93]
CNN (LS-AVPI)	Conv + Pool + FC + Dropout.	5	[182]
Lightweight CNN	5 Conv + 2 Pool + 2 FC.	9	[159]
CNN (Conv1D)	2 Conv1D + FC.	4	[177]
Dual-channel CNN (TCN-Att.)	3 Conv + 6 TCN + Self-Att. + FC.	13	[160]
CNN (under-sampled)	3 Conv1D + FC.	5	[172]
FCN + Self-Att.	3 Conv1D + Pool + Self-Att. + 2 FC.	9	[162]
Bayesian Conv-BLSTM	Conv1D + BLSTM + Att. + FC.	8	[67]
CNN-LSTM (NN-UWB)	2 Conv1D + Pool + LSTM + FC.	7	[90]
1D-CLANet	3 Conv1D + Pool + LSTM + SE-Att. + FC.	9	[188]
MTF-CNN	5 Conv2D + Pool + 3 FC.	8	[165]

Table 10. Summary of DNN architectures for ML-based UWB indoor localization.

DL Model	Architecture Summary	Depth	Reference
FNN	3 FC (50-50-50).	5	[8]
GA-RBF NN	RBF with 1 hidden (52).	3	[109]
FFNN	3 hidden (20-40-40).	6	[33]
DNN (TL)	2 FC nets (5 + 4).	5	[185]
DNN	3 FC + Softmax.	5	[106]
FFNN (BP)	1-4 hidden FC (3-15).	5	[114]
FCNN (Range)	3 FC (2040-1000-1000).	3	[111]
FCNN (Coord.)	3 FC (1000-1000-out).	3	[111]
GA-ELM	1 hidden + FC out.	3	[117]
Transfer Learning NN	2-stage DNN (5 + 4 FC).	5	[118]
HHO-BPNN	3 FC + sigmoid.	3	[136]
Lightweight FCNN	1 hidden (224).	3	[11]
BPNN	3 FC (4-9-4).	3	[183]
TinyML NN	1 hidden (20).	2	[123]
DBN	3 RBMs + BP fine-tuning.	6	[108]
DNN (VIUNet)	3 FC (256-256-3).	3	[105]
LTSSO-BPNN	1 hidden (13).	3	[68]
INDDNN	1D CNN (9 Conv + 8 Pool) + 5 FC.	23	[175]
DNN + TL	3 FC (256-256-2).	3	[166]
DFNN	3 hidden (100).	5	[161]
Optuna-LightGBM + DNN	4 hidden (10) per sub-area.	6	[63]
WF-BP NN	3 FC (7 hidden).	3	[91]
UKF-FNN-RIC	1 hidden (10).	3	[87]
DNN-EKF Fusion	3 hidden (50).	5	[102]
DNN (GWO-AOA)	2 hidden FC.	4	[132]
DNN + TL (range error)	4 FC + Dropout + BN.	6	[96]
DNN + TL (NLoS)	4 FC + Softmax.	5	[96]

The depth of the architectures varies widely depending on the task complexity and data modality. For CNN-based designs, the most common range lies between 5 and 9 layers, as in [30,50,145,189], balancing expressiveness and training cost. Deeper variants exceeding 10 layers, including residual and multi-stream models (e.g., FCN-Attention or Dual-Channel CNN-TCN networks [160,162]), appear in studies addressing complex multi-environment or multi-class NLoS identification, where hierarchical feature abstraction improves robustness. Lightweight CNNs with fewer than 5 layers are typically used in denoising or signal enhancement tasks (e.g., [93,177]).

In contrast, DNN-based architectures remain shallower, usually employing 3–6 fully connected layers (e.g., [106,111,161]). Their simplicity suits feature-based regression and classification, where CIR-derived parameters (e.g., power, delay spread, rise time) serve as compact inputs. However, some studies introduce metaheuristic optimization (e.g., LTSSO-BP [68], GWO-DNN [132]) or TL mechanisms [96,166] to enhance generalization with minimal architectural overhead. The deepest DNN design (23 layers) corresponds to the hybrid INDDNN model [175], combining CNN and dense layers for multi-class LoS/NLoS recognition, illustrating the convergence of CNN and DNN paradigms in recent work.

Figure 7 depicts the distribution of network depths across all surveyed studies. While CNNs span a broader range (3–21 layers), DNNs concentrate between 3 and 6 layers. This difference is primarily driven by input dimensionality: CNNs require deeper hierarchical structures to effectively extract spatial–temporal patterns from high-dimensional raw CIR waveforms. In contrast, DNNs typically operate on low-dimensional handcrafted features, such as peak power, rise time, or RSS, which can be effectively mapped to coordinates or classes using shallower architectures with fewer hidden layers, thereby reducing computational complexity for resource-constrained edge devices.

Moreover, architectures introduced after 2022 show a gradual shift toward hybrid models (e.g., CNN-LSTMs, CNN-Attention, or CNN-TCN) and fusion schemes (e.g., DNN-EKF or AE-CNN), where deep learning modules are embedded within traditional probabilistic or optimization-based frameworks to balance localization accuracy with computational efficiency.

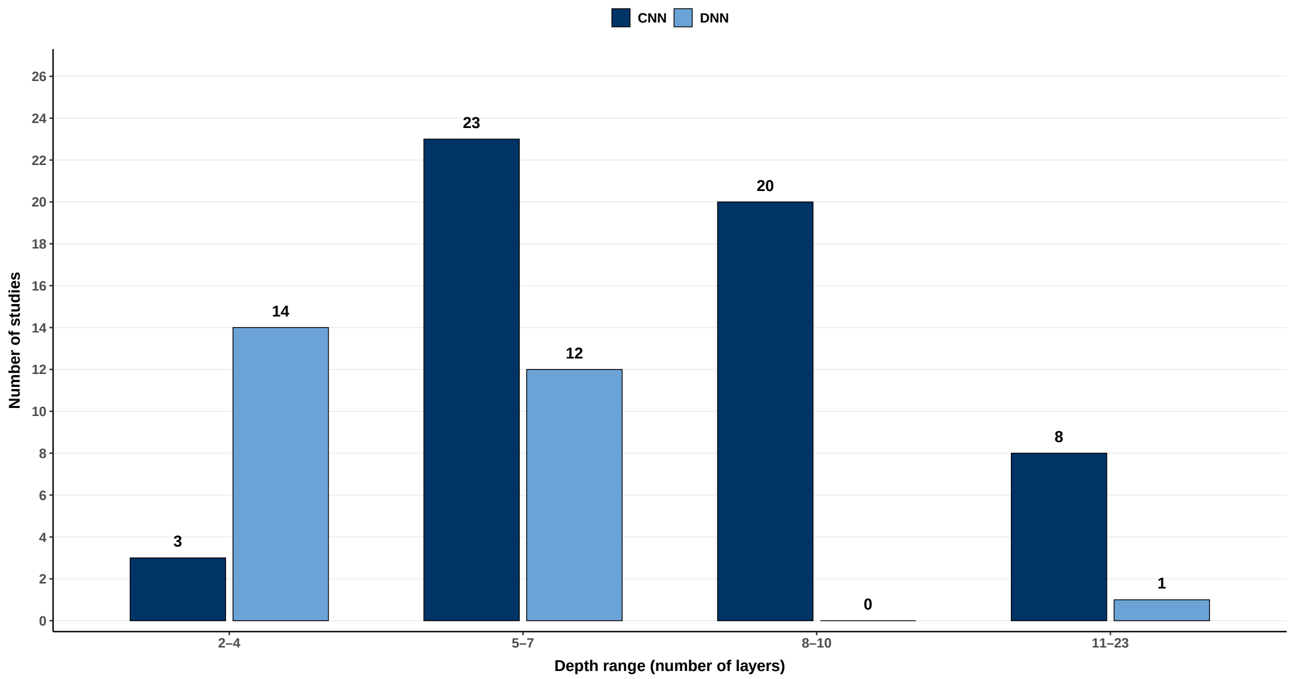

Figure 7. Distribution of CNN and DNN network depth in UWB localization studies (2020–2024).

In summary, CNN-based architectures dominate signal-level processing stages, providing robust spatial–temporal modeling, whereas DNNs remain central to post-processing and feature-based correction stages due to their simplicity, low latency, and adaptability to embedded implementations.

5.4. RQ3. How Are ML-Based UWB Positioning Methods Evaluated in Terms of Experimental Design, Performance Metrics, Validation Procedures, and Reproducibility?

To address RQ3, the evaluation of UWB-based systems incorporating ML is analyzed in terms of performance metrics, experimental setups, and reported outcomes. A total of 169 studies were reviewed and grouped according to their functional category: channel condition classification (83 studies), ranging error mitigation (60 studies), and position estimation (39 studies).

5.4.1. Reported Metrics

Regression-based studies predominantly used RMSE, and occasionally MAE, to quantify ranging or positioning accuracy. Classification-based studies mainly relied on Accuracy, followed by Precision, Recall, and F1-score for LoS/NLoS discrimination. A limited number of studies reported additional indicators such as bias, Standard Deviation (STD), or Cumulative Distribution Function (CDF) of error.

Figure 8 summarizes the relative frequency of each metric per task category, based on manual annotation of all 169 papers. As some studies contribute to multiple tasks in the pipeline, the metric counts reflect task-specific occurrences rather than unique articles.

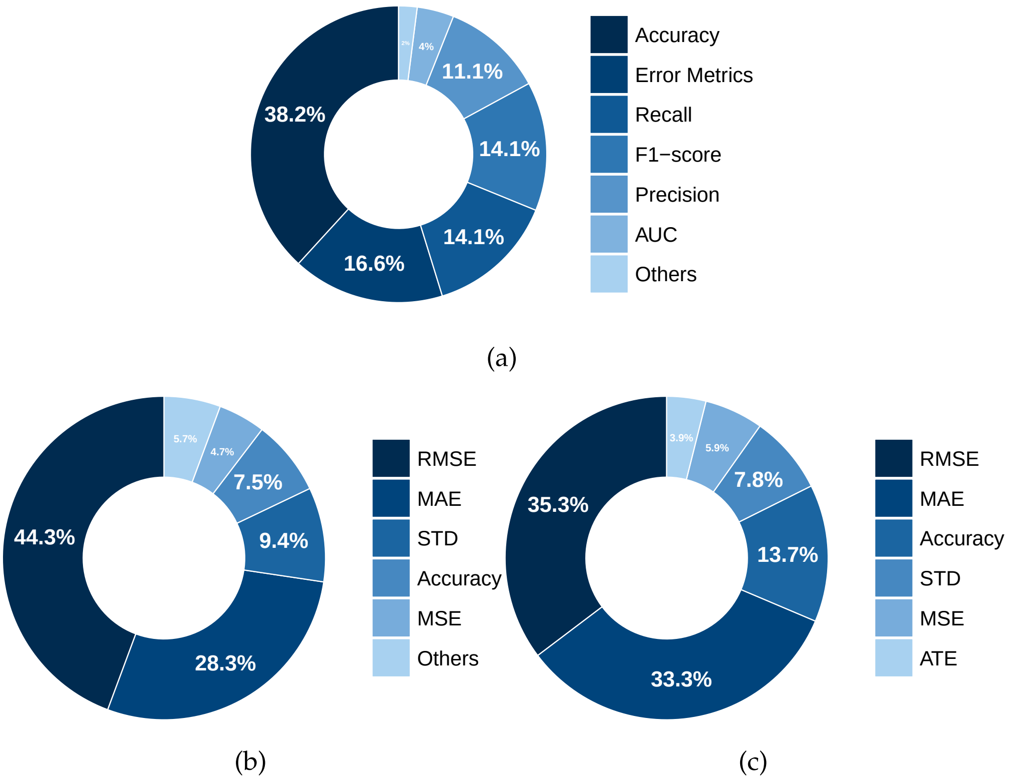

Figure 8. Distribution of evaluation metrics across the three ML stages: (**a**) channel condition identification, (**b**) ranging error mitigation, and (**c**) direct position estimation.

5.4.2. Observed Results

A summary of performance indicators and reported testbed areas is provided in Table 11. RMSE values below 0.2 m were common in controlled setups, while classification accuracy was above 95 % in most cases. Hybrid CNN–LSTMs or attention-based models achieved the highest performance levels. Due to overlapping processing stages, RMSE values often appear in both ranging and positioning categories.

Table 11. Performance metrics and reported experimental areas for ML-based UWB positioning tasks. Each range corresponds to studies explicitly reporting both metric values and testbed area.

Functional Task	Studies	Main Metric	Metric Range	Experimental Area
Channel condition classification	25 (area + metric)	Accuracy	81.4–100%	16–4420 m^2
Ranging error mitigation	31 (area + metric)	RMSE	0.0023–0.6242 m	16–1125 m^2
Position estimation	11 (area + metric)	RMSE	0.0091–0.6242 m	16–130 m^2

Note: "area + metric" indicates the subset of studies that explicitly reported both the performance metric and the physical area of the experimental testbed.

5.4.3. Experimental Configurations and Data Modalities

Experimental evaluations are predominantly conducted in controlled indoor environments, mainly laboratories and office-like spaces, typically covering areas smaller than 150 m^2. Large-scale deployments in warehouses, factories, or public buildings are comparatively rare, indicating a strong bias toward small- and medium-scale testbeds in the current literature.

From a hardware perspective, the Decawave (Qorvo) DW1000 transceiver family and its associated evaluation platforms (e.g., EVB1000, DWM1000/DWM1001, MDEK1001) dominate experimental configurations, accounting for approximately 90–95% of the reported systems.

More recent transceivers, such as the DW3000 series, appear only marginally in studies published after 2023, reflecting the inertia of established experimental platforms.

Regarding infrastructure design, the most common deployment consists of a single mobile tag and four fixed anchors arranged around the test area, balancing coverage and system complexity. Denser anchor configurations (six to eight anchors) are mainly reported in highly obstructed or industrial-like environments, while minimal setups with three anchors are typically restricted to constrained two-dimensional scenarios.

Ground truth acquisition follows heterogeneous methodologies. Dynamic experiments most frequently rely on high-precision optical motion-capture systems (e.g., OptiTrack or Vicon), whereas static evaluations often employ laser-based measurements, robotic total stations, or manually surveyed reference grids. For channel-condition studies, LoS/NLoS labels are commonly obtained through controlled obstacle placement, manual annotation, or synchronized reference systems, although labeling procedures are rarely standardized across studies.

From a data availability and reproducibility perspective, approximately 75–80% of the reviewed works rely on private or ad hoc datasets collected for a specific deployment, while only 20–25% explicitly employ publicly available benchmarks. Input data modalities vary substantially: most studies exploit raw UWB CIR information, either as amplitude-only samples or as complex-valued In-phase and Quadrature (IQ) representations, often complemented by timestamps, ToF estimates, RSS, and proprietary diagnostic features.

Among the available open resources, the dataset released by Stocker et al. [191] (TU Graz) is particularly relevant for commercial IPS deployments. It addresses the ambiguity between LoS and NLoS conditions by introducing a Weak Line-of-Sight (WLoS) category for minor obstructions.

Public datasets typically report anchor-tag configurations ranging from single-anchor setups to networks of up to nine anchors, but environmental diversity remains limited. This heterogeneity in experimental design, data modalities, and labeling procedures directly constrains the reproducibility and comparability of reported results across the state of the art.

5.4.4. Reporting Consistency

Approximately 60% of studies did not specify essential details such as the testbed area, anchor geometry, or the computation procedure for RMSE or Accuracy. Only a minority of works provided full reproducibility information, including environment dimensions and measurement protocols, limiting quantitative comparison between studies.

5.4.5. Implications and Observed Limitations

The dominance of RMSE and Accuracy as reporting metrics simplifies benchmarking; however, only a subset of papers provided both performance metrics and testbed area (25 for classification, 31 for ranging correction, and 11 for positioning). As a consequence, the generalizability of reported improvements remains constrained by incomplete documentation.

These inconsistencies hinder a fair assessment of how ML methods contribute to UWB localization performance. Without standardized evaluation protocols and complete metadata, it is difficult to isolate the benefit of the learning model from that of the experimental conditions.

Overall, the findings from RQ3 show that current evaluation practices strongly condition the interpretation of ML contributions to UWB-based IPSs. Future studies would benefit from clearer reporting standards and unified benchmarking frameworks, enabling greater transparency and reproducibility across environments and acquisition setups.

5.5. RQ4. What Public Datasets or Benchmarks Are Available for Combining UWB and ML, and How Are They Used to Improve the Reproducibility and Comparability of Results?

Only a limited number of studies explicitly report the use of publicly available datasets for UWB-ML experimentation. These open resources provide the foundation for reproducible benchmarking. A structured summary of these datasets, explicitly detailing data modalities (e.g., amplitude vs. complex IQ), anchor-tag configurations, environmental conditions, and ground truth acquisition procedures, is provided in Table 12. These datasets address several reproducibility gaps identified in RQ3 by offering standardized benchmarks for comparison.

Table 12. Public datasets and benchmarks used for ML-based UWB localization. The table details input data modalities, hardware platforms, and the ground truth acquisition methodology.

Dataset	Year	Content: Input, Hardware & Ground Truth	Environment	Representative Usage
eWINE (Log-a-Tec) [192]	2016–2023	CIR (Amp. & Complex IQ), ToF, RSS. Hardware: Decawave DW1000. Ground Truth: Optical Mocap & Laser.	Lab, apartment, office, workshop	[30,39,53,54,88,144,162]
DeepUWB [193]	2020	CIR (157 samples), range, features. Hardware: Decawave EVB1000. Ground Truth: Laser distance meter.	Lab, Industrial (metal/glass)	[61,71,144]
Stocker et al. (TU Graz) [191]	2021	Raw CIR & Chip Diagnostics. Labels: LoS/WLoS/NLoS. Hardware: Decawave DWM1001. Ground Truth: Leica Total Station.	Office, Lab, Corridor (35k samples)	[61,139,157]
Bielefeld Univ. [52]	2020	CIR features & RSS. Labels: LoS/NLoS/Multipath. Hardware: Decawave DW1000. Ground Truth: Manual grid.	Corridors, Halls	[52,175]
Datasets of Indoor UWB [194]	2022	Ranging data & CIR. Hardware: Decawave MDEK1001. Ground Truth: Known anchor positions.	Office, Laboratory	[95]
LocURa4IoT [195]	2021	ToF, CIR, RSS, clock-skew. Hardware: IEEE 802.15.4 UWB nodes. Ground Truth: Pre-surveyed grid.	Controlled IoT testbed	[132]
IPIN 2021 Track 7 [196]	2021	Complex CIR (IQ) & Range. Hardware: Decawave DW1000. Ground Truth: Millimeter-accurate Optical Mocap.	Industrial hall (300 m^2)	[9]
ETH Zürich Radar [197]	2020	Multi-static Radar CIR. Hardware: DW1000 (Radar mode). Ground Truth: Vicon Optical Mocap.	Laboratory (50 m^2)	[10]
Other public datasets	2019–2024	Open datasets for RSS-based ranging, trust, fingerprinting and cooperative loc.	Office, Industrial	[76,83,135,186]

The eWINE-project dataset [192] is the most frequently reused benchmark for LoS/NLoS classification in UWB-based ML. Originally collected in 2018 within the European H2020 eWINE project at the Jožef Stefan Institute, it was released on Zenodo between 2021 and 2023 in several versions. The dataset contains 42,000 CIR and ToF samples acquired with nine Decawave DW1000 transceivers across four indoor environments (laboratory, office, apartment, and workshop). It includes anchor coordinates, LoS/NLoS annotations, and reference tag trajectories, supporting reproducible evaluation of DNN for channel classification and bias correction. Several studies explicitly state their use of this dataset, including [30,39,53,54,59,69,85,88,141,144,150,152,155,160,162,180]. The eWINE collection has thus become the de facto open benchmark for DL-based LoS/NLoS identification and NLoS bias mitigation in UWB localization.

The DeepUWB dataset [193], introduced in 2020, was designed to support reproducible research on range-error mitigation. It includes more than 55,000 CIR traces (157 features per record) collected with Decawave EVB1000 transceivers and labeled with laser-based ground truth ranges. The data were gathered across five configurations, three indoor rooms of different sizes, one cross-room setup, and one outdoor environment, each with multiple obstacle types (walls, plywood, glass, plastic, and metal). DeepUWB has been reused in several works addressing learning-based range correction and feature-selection strategies [61,71,74,141,144].

The Bielefeld University dataset [52], published as Supplementary Research Data for the Paper entitled Identification of NLoS and Multipath Conditions in UWB Localization using ML methods, provides extracted UWB signal features labeled as LoS, NLoS, and multipath conditions. It also includes source code for scikit-learn-based classifiers. The dataset was collected in university corridors and laboratory environments and has been reused in later studies on multi-class channel-state classification and TL [52,175,176].

The LocURa4IoT dataset [195], developed by Adrien Van Den Bossche, Réjane Dalcé, Quentin Vey, and Thierry Val at IRIT/CNRS Toulouse, comprises a series of open-access datasets dedicated to the precise localization of wireless nodes in IoT environments. The experiments, performed between 2021 and 2022, include ToF-based ranging data collected with IEEE 802.15.4 UWB transceivers under both LoS and NLoS conditions. Each dataset contains JSON-formatted logs with timestamps, range errors, clock skew, RSS, CIR samples, and 3D anchor-tag coordinates. These datasets have been explicitly used in [132] to train and benchmark DL models optimized via meta-heuristic algorithms for indoor localization.

The IPIN 2021 Track 7 dataset [196], created by Sebastian Kram, Maximilian Stahlke, and Christopher Mutschler at Fraunhofer IIS/FAU Erlangen–Nürnberg, contains synchronized complex CIR measurements (real + imaginary) and millimeter-accurate ground truth trajectories acquired with Decawave DW1000 transceivers. The experiments were conducted in an industrial hall of about 300 m^2 under two conditions (static and modified clutter), enabling the evaluation of localization robustness and generalization. It has been reused in studies on CIR-based fingerprinting and error mitigation [9].

The dataset released by Stocker et al. [191] (TU Graz) is particularly relevant for commercial IPS deployments. It addresses the ambiguity between LoS and NLoS conditions by introducing a WLoS category for minor obstructions. Collected using commercial Decawave DWM1001-DEV nodes, it provides over 35,000 ranging measurements. Due to its use of commercial hardware and precise labeling, this dataset has been widely adopted in recent ML studies for channel state identification and error mitigation [61,139,157].

The ETH Zürich dataset [197], published in 2020 by Anton Ledergerber and Raffaello D'Andrea, provides multi-static UWB radar measurements with synchronized ground truth obtained via a Vicon motion-capture system. The data include complex CIR samples (DW1000 transceivers) and 3D trajectories for multiple transmitter–receiver pairs (IDs 0–4). Experiments were conducted in a controlled laboratory environment of about 50 m^2, enabling high-precision analysis of ToF estimation and AoA inference [10].

The UTIL dataset [198], released in 2022, provides UWB TDoA measurements for graph-based and multi-agent indoor localization. It has been primarily used in recent works employing GATs and neural message-passing architectures for cooperative UWB positioning [135].

Additional publicly available datasets further enhance reproducibility in UWB-ML research. Josep Moragrega [95,194] published the Datasets of Indoor UWB Measurements for Ranging and Positioning in Good and Challenging Scenarios on Zenodo, while David Botler [76,199] released three RSS-based UWB datasets for distance estimation. Matthias Peterseil [83] made available the UWB WLoS structured dataset and the UWB AEC-trust dataset, and Dominik Csik [186] released a multimodal fingerprinting dataset integrating Wi-Fi, UWB, and RSS features. Muhammad Fahem Majeed [175] contributed the UWB DW1000 Dataset for Indoor Environments on IEEE DataPort, while Pieter Fontaine [28] released the Industrial-UWB-localization-CIR-dataset, an industrial-hall benchmark widely used for CIR-based fingerprinting and TL.

Together, these open datasets have progressively improved traceability and comparability in UWB-based ML research. Their increasing adoption since 2020 has fostered more transparent evaluation practices, paving the way for standardized benchmarks for future indoor positioning studies.

Dataset Limitations, Standardization, and Benchmarking

Beyond the increasing availability of open data, the reviewed literature reveals significant challenges regarding the utility and systematic standardization of existing datasets. Three major issues currently impede the reproducibility and cross-study comparability of ML-based UWB research:

Site-Specificity and Hardware Dependency: A pervasive limitation is the strong environmental bias in training data. Models trained on datasets collected in specific layouts, such as laboratories or offices, often suffer significant performance degradation when deployed in unseen environments due to differing multipath profiles [50,96]. Furthermore, the overwhelming dominance of the Decawave DW1000 chip in public repositories limits the assessment of model robustness across different hardware vendors, pulse shapes, or newer Institute of Electrical and Electronics Engineers (IEEE) 802.15.4z-compliant transceivers.

Lack of Data Representation Standards: There is no unified format for representing UWB signal features. While some datasets provide the full 1016-sample CIR, others offer truncated windows around the first path or transformed 2D representations, such as wavelet or Gramian fields [38,174]. This heterogeneity in pre-processing pipelines makes it difficult to conduct fair performance comparisons, as the input dimensionality and signal-to-noise ratio vary significantly across studies. Moreover, the lack of information regarding the quantization and sampling rates of the recorded CIR further complicates the normalization of data across heterogeneous hardware.

Limited Cross-Algorithm Benchmarking: Despite the emergence of datasets like eWINE [192] and DeepUWB [193] as de facto benchmarks, cross-algorithm validation remains the exception rather than the rule. Most authors continue to validate novel architectures on proprietary, non-public data, which prevents the research community from establishing a clear state-of-the-art for specific positioning tasks.

Addressing these shortcomings through unified data formats and the adoption of cross-environment validation protocols is essential to move the field beyond site-specific proofs of concept toward generalizable positioning solutions.

5.6. RQ5. What Are the Main Challenges, Limitations, and Open Issues Identified in Applying ML to UWB-Based Indoor Positioning, and What Directions for Future Research Are Suggested?

5.6.1. Main Challenges and Limitations

The reviewed studies reveal several persistent challenges in the application of ML to UWB-based indoor positioning. These challenges arise both from the intrinsic properties of UWB propagation and from practical constraints associated with data-driven model design and deployment.

Intrinsic UWB signal issues: The primary limitation originates from the NLoS phenomenon and multipath propagation effects. NLoS conditions introduce a positive ranging bias. Reflected signals travel longer paths than direct ones, producing deviations that can exceed one meter. Complex and dynamic indoor environments, characterized by walls, furniture, and moving people, further distort the CIR. Moreover, similar CIR patterns can yield different ranging errors and conversely, similar errors can arise from dissimilar CIRs, which complicates model training and reduces prediction consistency.

Data collection and training limitations: The performance of ML algorithms strongly depends on large, high-quality datasets, although collecting such data is costly and time-consuming. Fingerprinting-based approaches require dense measurement campaigns, particularly in large-scale environments. Obtaining reliable ground truth positions for supervised training often demands external high-precision systems such as Light Detection and Ranging (LiDAR) or motion-capture setups. Class imbalance is another recurring issue: LoS samples are typically much more abundant than NLoS ones, leading to biased models that perform poorly under challenging propagation conditions.

Generalization and robustness: Most ML models are site-specific and exhibit limited transferability to unseen environments. Variations in room geometry, antenna configuration, and multipath characteristics cause performance degradation when models are applied to new settings. Furthermore, the dominance of binary LoS/NLoS classification oversimplifies real-world conditions, neglecting intermediate or mixed cases such as hard NLoS or obstacle-type differentiation.

Computational and deployment constraints: High model complexity restricts real-time deployment on low-power UWB devices. Deep architectures designed for accuracy often require heavy computation and large memory. Embedded hardware such as microcontrollers or edge nodes often fail to sustain inference at high update rates. In addition, preprocessing stages, such as transforming CIR data into image-like formats, introduce additional computational overhead and latency, limiting real-time operation.

5.6.2. Future Research Directions

Based on the synthesis of the reviewed studies, the path for new research in this field should transition from generic exploration toward specific objectives aimed at overcoming current technical bottlenecks. We propose a research roadmap structured around four strategic phases:

Phase 1: Advanced Signal Preprocessing (Generative and Unsupervised): To address the scarcity and imbalance of NLoS data, research is shifting toward the use of GANs for synthetic CIR generation [48] and few-shot environment adaptation [149]. Furthermore, transforming 1D signals into 2D representations using Gramian Angular Fields (GAFs) [38,79] or Complex Gaussian Wavelets [160] is recommended to better exploit the hierarchical feature extraction capabilities of ResNet-like architectures. Finally, unsupervised integrity monitoring using VAEs [36,171] or LSTMs-based AEs [83] should be prioritized to generate real-time trustworthiness scores and detect signal manipulation.

Phase 2: Semantic Classification and Domain Adaptation: Future work must move beyond binary LoS/NLoS identification toward semantic context awareness, identifying specific materials (e.g., concrete, glass, or metal) to apply material-specific bias corrections [47,67,90]. To solve the site-specificity problem, research should prioritize DA using Domain Adversarial Neural Networks (DANNs) [181] and Lab-to-Real transfer strategies [166]. For practical deployment, Tiny Machine Learning (TinyML) strategies using quantization and pruning [61,71,123] are essential to enable ML inference on microcontrollers with sub-millisecond latency.

Phase 3: Probabilistic and Hybrid Error Mitigation: To prevent inconsistent corrections, future models should focus on uncertainty quantification using Monte Carlo Dropout [67] or Stochastic Variational Gaussian Processs (SVGPs) [75]. This allows hybrid architectures to dynamically adjust the noise covariance matrices (Q and R) of filters like the EKF or Pose Graphs [36,103,158]. Additionally, self-supervised learning using geometric residuals [35,126] offers a path to refine error models in situ without requiring manual ground truth labeling.

Phase 4: Next-Generation Positioning (Graph and Attention Models): To model complex spatial relationships between anchors and tags, the adoption of GATs [135] and spatial–temporal GNNs [129,130] is recommended. For sequential tracking, Transformer-based encoders [54,128] and BERT-style architectures [167] show superior capacity over LSTMss for capturing long-range dependencies in CIR sequences. Finally, deep multi-modal fusion (e.g., VIU-Net [105] or Deep Belief Network (DBN)-based systems [108]) should be explored to integrate UWB, vision, and inertial data at the latent feature level.

In summary, while generalization across environments remains the dominant challenge, emerging advances in TL, attention mechanisms, and lightweight embedded implementations indicate a transition toward more robust and adaptive UWB localization systems.

6. Discussion

This section discusses and interprets the findings of this systematic review according to the MRQ and the five specific RQs (RQ1–RQ5) defined in Section 4. It synthesizes the empirical patterns identified in Section 5 and interprets them in terms of how ML contributes to accuracy, robustness, and adaptability in UWB-based positioning systems.

6.1. MRQ. How Do ML Algorithms Contribute to UWB-Based Indoor Positioning Systems?

This review shows that ML enhances UWB indoor positioning by improving signal interpretation, mitigating range errors, and strengthening decision-making stages such as channel classification and coordinate estimation. Rather than replacing traditional geometric methods, ML is typically integrated as a complementary module that models nonlinearities and uncertainties in the CIR. This hybridization between physics-based and data-driven approaches has demonstrated promising improvements in reducing NLoS bias and achieving decimeter-level or even centimeter-level accuracy under complex propagation conditions. However, current evidence indicates that the most consistent benefits arise when ML is used to support, not replace, traditional solvers, reinforcing the need for interpretable and computationally efficient hybrid architectures.

6.2. RQ1. What Specific Tasks or Functions Within the Pipeline of UWB-Based Indoor Positioning Systems Are Addressed Through ML Algorithms?

The analysis identified six major functional tasks in which ML techniques have been applied: signal denoising and preprocessing, channel condition classification (LoS/NLoS), ranging error mitigation, data fusion or hybridization, position estimation, and sequential tracking. As evidenced by the results, the majority of studies concentrate on channel classification and ranging error mitigation. This confirms that ML currently plays a primarily supporting role, acting as a non-linear compensator for physical-layer impairments before measurements are fed into traditional geometric solvers.

A critical conceptual distinction emerges from how these tasks address multipath propagation. The literature reveals two contrasting design paradigms:

Multipath Suppression: Traditional ranging approaches and error mitigation tasks generally view multipath and NLoS reflections as impairments to be removed. In this paradigm, ML models are trained to recover the first-path arrival or compensate for the resulting positive bias, treating reflections as unwanted noise [71,179].

Multipath Exploitation: Conversely, positioning and fingerprinting tasks increasingly leverage multipath components as valuable spatial features. In this paradigm, the rich structure of the full CIR, including delayed reflections, is interpreted as a location-dependent signature (e.g., utilizing reflections as virtual anchors), allowing DL models to capture complex dependencies that correlate with specific coordinates [96,142].

From an engineering perspective, the choice between suppression and exploitation depends on deployment constraints. While suppression is more compatible with existing geometric infrastructures (Pipeline a), exploitation via CIR-based fingerprinting (Pipeline c) offers superior robustness in sparse anchor deployments, albeit at the cost of higher model complexity and site-specific training.

Finally, while geometric multilateration remains the dominant approach, the emergence of direct position estimation frameworks capable of mapping signal features directly to coordinates suggests a promising direction to reduce cumulative error propagation and improve the overall resilience of IPSs.

6.3. RQ2. Which ML Algorithms Are Most Commonly Applied to These Tasks, and What Motivations or Advantages Are Reported in the Literature to Justify Their Use?

DNNs, particularly CNNs and hybrid CNN-LSTMs architectures, are the most frequent models applied in UWB-based positioning pipelines. They are followed by AEs, MLPs, and classical algorithms such as RFs, SVMs, GMMs, and Naïve Bayes classifiers. CNNs are widely used for extracting spatial and temporal features from CIR data, while LSTMs variants are employed when sequential dependencies are relevant. AEs and GAN-based models are increasingly adopted for feature compression and synthetic data generation. Authors typically justify their use based on the accuracy improvements and robustness achieved under multipath and NLoS conditions, although aspects such as model interpretability, computational complexity, and hardware feasibility are often overlooked. Transformer-based architectures have started to appear and show significant potential for unified spatial–temporal representation learning, although their adoption is still limited by computational costs and the scarcity of large annotated datasets.

While DL dominates the current landscape, the field remains in an exploratory stage where model selection is often empirical rather than guided by systematic benchmarking. To assist practitioners, Table 13 aggregates performance ranges segregated into two domains: Accuracy for classification and RMSE for regression (ranging/positioning).

The data, derived from the experimental results of the 169 analyzed papers, indicates a clear trade-off between accuracy and complexity. DL models (specifically CNNs and LSTMss) consistently achieve state-of-the-art accuracy, particularly in complex NLoS classification and dynamic tracking (RMSE $<$ 15 cm). However, classical models like SVMs and RFs remain highly competitive, often reaching accuracies above 95% with significantly lower computational latency, offering a balanced trade-off for embedded applications.

Table 13. Summary of typical performance ranges and application suitability for key ML algorithms in UWB positioning (2020–2024). Bold face indicates the overall best performance achieved for each major task.

Task	Algorithm	Observed Performance	Best Suited For
Channel Classification	CNN/ResNet/TCN	Acc: 82.6–**100.0**% [38,45]	High-end hardware, raw CIR inputs.
	Hybrid (CNN–LSTMs)	Acc: 82.2–98.5% [58,150]	Spatio-temporal signal dynamics.
	SVM/Naïve Bayes	Acc: 78.3–99.8% [41,61]	Low-power MCUs, small datasets.
	Tree-based (RF/XGBoost)	Acc: 82.8–99.5% [164,176]	Robust handcrafted feature classification.
	Transformers/DNN	Acc: 81.4–**100.0**% [54,158]	Global context and deep feature learning.
Error Mitigation	AE/VAE	RMSE: 0.103–0.600 m [36,103]	Unsupervised noise removal.
	Deep Regressors	RMSE: 0.001–0.367 m [6,63]	High-precision bias correction.
	Classical/Prob.	RMSE: **0.001**–0.545 m [67,100]	GMM, GPR, or GP probabilistic modeling.
	Ensemble Methods	RMSE: 0.022–0.624 m [11,108]	Robust feature-based regression.
	Clustering	RMSE: 0.017–0.555 m [65,101]	Selection of LoS/NLoS measurements.
Position Estimation	LSTMs/GRU	RMSE: **0.008**–0.139 m [113,120]	Dynamic tracking and trajectory smoothing.
	Direct CNN/DNN	RMSE: 0.009–0.204 m [125,133]	Snapshot positioning and complex mapping.
	Classical/Hybrid	RMSE: 0.020–3.342 m [108,110]	Static or resource-constrained deployments.

Performance Comparison: ML vs. Classical Baselines

A critical motivation for adopting ML identified in this review lies in its ability to overcome the systematic limitations of classical estimators. While classical analytical models dominate in clean LoS environments due to their predictability and low computational cost, the literature consistently reports that ML provides measurable advantages when geometric assumptions fail.

Quantitative comparisons indicate that chip-integrated LDE algorithms degrade severely under NLoS conditions, as the FP is often attenuated below the detection threshold. Learning-based regressors operating on raw CIR data exploit multipath structure rather than suppressing it, achieving ranging error reductions between 20–35% compared to standard LDE in unseen test conditions [92,185]. Unlike polynomial bias models, which are often restricted to specific antenna orientations, ML models demonstrate superior capacity to learn orientation-invariant feature representations.

Regarding angular estimation, classical super-resolution methods such as Multiple Signal Classification (MUSIC) or Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT) suffer from a loss of subspace orthogonality in dense multipath environments. Recent studies demonstrate that DL models improve robustness by acting as a pre-processing denoiser or feature enhancer, restoring the Signal-to-Noise Ratio (SNR) required for MUSIC to operate reliably [137,146].

Finally, a clear distinction emerges in tracking tasks. Pure sequence-based models (e.g., LSTMs) can outperform classical EKF solutions during momentary signal outages or severe IMU drift [99]. However, hybrid architectures, where ML dynamically adapts the EKF noise covariance matrix (Q and R tuning), consistently provide the best trade-off between accuracy, stability, and generalization [58].

6.4. RQ3. How Are ML-Based UWB Positioning Methods Evaluated in Terms of Experimental Design, Performance Metrics, Validation Procedures, and Reproducibility?

The evaluation of ML-based UWB systems remains highly heterogeneous. Most studies assess performance using task-specific metrics: RMSE and MAE for regression (ranging and positioning), and Accuracy, Precision, Recall, or F1-score for channel classification. A smaller subset of works includes computational complexity and latency, which are critical for real-time feasibility. Experimental setups are predominantly restricted to small-scale indoor environments (<15 m^2), such as offices or laboratories, typically employing four to six anchors. The prevalence of ad hoc datasets and the lack of standardized reporting formats hinder reproducibility and cross-study comparability. Currently, only a minority of studies explicitly adhere to recognized benchmarking frameworks such as the International Organization for Standardization (ISO)/International Electrotechnical Commission (IEC) 18305 standard.

Despite these inconsistencies, the literature consistently reports that ML modules provide a measurable advantage over conventional geometric filters, reducing ranging errors by approximately 20–50% and improving classification accuracy by 5–10 percentage points. However, the magnitude of these gains varies substantially across environments, reinforcing the need for unified benchmarking protocols (see Table 11).

6.4.1. Industrial Standards Compatibility

ML methods applied to UWB-based localization are not standardized as standalone algorithms. Instead, they operate as enhancement layers for hardware that complies with strict industrial standards. Adherence to these standards is essential for commercial viability. At the physical layer, the IEEE 802.15.4 family remains the normative foundation. The majority of reviewed studies rely on CIR samples or ToF estimates generated according to these specifications. Furthermore, the IEEE 802.15.4a channel models (CM1–CM8) are vital for standardized simulation and pre-training. A summary of these industrial standards and their specific implications for ML methods is provided in Table 14.

At the physical and medium access layers, the IEEE 802.15.4 family constitutes the normative foundation. The majority of reviewed studies rely on CIR samples, ToF estimates, or phase information generated according to IEEE 802.15.4 specifications. As a consequence, ML models are implicitly constrained by standardized PHY parameters such as preamble length and timestamping resolution. Furthermore, the IEEE 802.15.4a Channel Models (CM1–CM8) play a crucial role in ML research, enabling standardized simulation of multipath propagation for pre-training deep networks.

Recent amendments, notably IEEE 802.15.4z, introduce security features like the Scrambled Timestamp Sequence (STS). From an ML perspective, these are particularly relevant for trustworthiness assessment and spoofing detection. Interoperability frameworks, such as the Fine Ranging (FiRa) Consortium, ensure cross-vendor compatibility where ML-based NLoS detection can be integrated as a post-processing module within certified stacks. Additionally, performance requirements from the 3GPP (for 5G/IoT positioning) and regulatory limits from the Federal Communications Commission (FCC)/European Telecommunications Standards Institute (ETSI) (on power spectral density) dictate the low-SNR conditions under which ML models must remain robust.

Table 14. Relevant industrial standards and their implications for ML-based UWB localization.

Standard	Scope	Implications for ML Methods
IEEE 802.15.4/4a	PHY/Channel models	Standardized CIR structure and propagation models for training.
IEEE 802.15.4z	Secure ranging	Introduces STS and PDoA, enabling ML-based security assessment.
FiRa Consortium	Interoperability	Ensures compatibility; ML acts as a post-processing enhancement.
3GPP	Requirements	Defines accuracy and latency targets for 5G and IoT localization.
FCC/ETSI	Regulation	Imposes PSD limits, requiring models robust to low-SNR.

6.4.2. Temporal Dynamics and Sequential Modeling

A significant trend identified in this review is the increasing reliance on sequential models to capture the temporal dynamics of user motion and channel evolution. Unlike static models, these architectures maintain an internal state, allowing the system to distinguish transient NLoS spikes from plausible movement. While LSTMss and GRUs remain the standard for modeling temporal dependencies in trajectories [99,113], the state of the art is transitioning toward Transformer-based architectures. These models excel at capturing long-range dependencies and global context from raw CIRs, often outperforming convolutional baselines in complex industrial environments [54,167].

6.5. RQ4. What Public Datasets or Benchmarks Are Available for Combining UWB and ML, and How Are They Used to Improve the Reproducibility and Comparability of Results?

The review reveals that publicly available datasets for UWB-ML research remains scarce, significantly limiting reproducibility and cross-comparison across studies. Existing benchmarks (summarized in Table 12) provide valuable resources for channel classification and range-error mitigation, covering diverse raw data modalities (e.g., amplitude vs. complex IQ CIRs), anchor densities, and ground-truth methodologies. However, their scope and scale remain limited compared to the environmental variability found in real-world industrial deployments. Most studies continue to rely on proprietary or small-scale data, restricting progress toward standardized evaluation. This imbalance between private and public datasets likely explains the inconsistencies observed in reported performance and the limited generalizability of current ML-based UWB positioning methods.

The scarcity of public datasets identified in this review represents more than a simple lack of resources; it is a fundamental barrier to the maturation of the field. Without standardized, multi-environment benchmarks, the community cannot effectively address the site-specificity problem. Most reviewed models are validated on data collected in a single laboratory or office, making it impossible to determine if the reported centimeter-level accuracy is a result of a robust model architecture or simply the result of overfitting to the local multipath profile. Future progress in the field will depend on the adoption of open-science practices, where authors release raw CIRs alongside their coordinate ground-truth to enable transparent and replicable research.

6.6. RQ5. What Are the Main Challenges, Limitations, and Open Issues Identified in Applying ML to UWB-Based Indoor Positioning, and What Directions for Future Research Are Suggested?

The review identifies four major categories of challenges: signal-related issues (multipath and NLoS), data limitations (scarcity and imbalance), generalization problems (site-specificity), and deployment constraints. While the first three are intrinsic to the physics of UWB or the training process, the latter represents a decisive engineering barrier for real-world adoption.

6.6.1. Computational Constraints and Deployment Feasibility

The reviewed literature reveals a clear gap between algorithmic performance and deployment feasibility on resource-constrained edge devices. These limitations can be categorized into algorithmic complexity and hardware constraints:

- Algorithmic Complexity: The computational cost, expressed in Floating-Point Operations (FLOPs) and parameter count, directly dictates latency. Deep architectures such as stacked LSTMss typically require orders of magnitude more operations than lightweight CNNs. Comparative analyses show that an LSTMs-based model may require 10–15 MFLOPs per inference, whereas a compact CNN can operate below 1 MFLOP under similar conditions, enabling high-rate tracking on standard microcontrollers.
- Feature Extraction Bottleneck: Processing the full raw CIR often dominates latency. Extracting complex handcrafted features can take tens of milliseconds on low-power MCUs, whereas reducing the CIR window or using learned embeddings allows for sub-millisecond execution.
- Hardware and Memory: Unoptimized DL models often exceed the flash/RAM budgets of Cortex-M class microcontrollers. Studies demonstrate that quantization (FP32

to INT8) is essential, reducing memory footprints by nearly an order of magnitude with minimal accuracy loss.
- Energy Efficiency: Executing deep models on general-purpose Central Processing Units (CPUs) is energy-intensive. Hardware acceleration using Field-Programmable Gate Arrays (FPGAs) or dedicated edge Artificial Intelligence (AI) accelerators (e.g., Edge Tensor Processing Unit (TPU)) has been reported to reduce energy per inference by more than 10× compared to software-based execution.

6.6.2. Security, Privacy, and Adversarial Robustness

While the primary focus of the reviewed literature is the mitigation of natural environmental errors, the integration of ML into UWB systems also raises critical considerations regarding security. Insufficient cyber–physical security can compromise localization accuracy to a degree comparable to severe propagation impairments.

A limited number of studies explicitly address such threats. For instance, Peterseil et al. [83] highlight the vulnerability of UWB to physical-layer attacks such as Cicada (preamble manipulation), proposing ML-based AEs to derive a trustworthiness score. Similarly, Botler et al. [76] investigate distance enlargement fraud, demonstrating that hybrid frameworks combining ToF and RSS can enforce geometric constraints to detect spoofing.

Crucially, the emergence of the IEEE 802.15.4z standard, which introduces the STS, provides a critical hardware-level defense. Future research must ensure that ML-based modules are aware of these security features; otherwise, unconstrained learning models might inadvertently "correct" (and thus validate) signal distortions caused by malicious distance-bounding violations, mistaking them for natural multipath effects.

Regarding privacy, the adoption of edge computing, discussed in Section 6.6.1, offers inherent advantages. Processing UWB data locally on embedded devices [28,32] reduces the need to transmit sensitive raw channel information to external servers, supporting privacy-by-design principles.

6.6.3. Future Research Roadmap

The next stage of progress will depend on bridging the gap between algorithmic innovation and system-level integration. Future research should prioritize:

1. Hybrid Physics–ML Architectures: Combining analytical propagation models with data-driven inference to improve interpretability.
2. Robust Feature Extraction: Developing orientation-invariant features that survive the move from laboratory to industrial environments.
3. Decentralized Learning: Utilizing DA, TL, and Federated Learning (FL) to improve generalization while ensuring privacy compliance.

6.7. Overall Discussion and Implications

Across all RQs, the review reveals a transition from handcrafted modeling toward data-driven learning in UWB indoor positioning. ML techniques have proven effective in mitigating ranging bias, improving classification accuracy, and enhancing overall robustness; however, reproducibility, dataset standardization, and scalability remain the primary open challenges. The integration of ML into UWB positioning is still fragmented across isolated tasks, but the growing convergence toward hybrid and fully integrated frameworks indicates a maturing research field.

Future progress will rely on the availability of unified open datasets, standardized evaluation protocols, and efficient models capable of balancing accuracy, latency, and energy constraints, ultimately enabling scalable, adaptive, and interoperable IPSs.

This momentum continues into 2025, validating the Actionable Research Roadmap proposed in Section 5.6.2. Very recent studies confirm the shift toward Transformer-based architectures for global temporal modeling [200] and deep sensor fusion using advanced recurrent units for industrial tracking [201]. Furthermore, the push for generalization is actively being addressed through DA frameworks such as AdaLoS [202], while the demand for edge efficiency has led to novel lightweight architectures such as LightMamba [203], which optimizes state-space modeling for resource-constrained devices. These contributions underscore that the field is rapidly evolving from static accuracy improvements toward more robust, efficient, and context-aware localization systems.

7. Conclusions

This comprehensive review provides a synthesis of the role of ML in UWB-based IPS technologies, analyzing 169 primary studies through the PRISMA framework. Our findings demonstrate that ML has become a fundamental tool for enhancing positioning accuracy and robustness, primarily by mitigating multipath and NLoS effects through channel classification and ranging bias correction. The transition from classical models like SVM and RF toward deep architectures, particularly CNNs and hybrid CNN-LSTMss, underscores a growing capacity to model the complex, nonlinear behavior of the UWB channel impulse response. Despite these technical gains, the review highlights significant gaps in evaluation consistency and data standardization, where the reliance on site-specific, private datasets remains a decisive barrier to the reproducibility and industrial scalability of the proposed solutions.

To bridge these gaps, the path for future research should transition from generic exploration toward specific, actionable objectives. Our proposed roadmap emphasizes four strategic areas: advanced generative preprocessing for dataset balancing, semantic classification through domain adaptation to improve generalization, probabilistic error mitigation for uncertainty quantification, and the adoption of next-generation architectures like GNNs and Transformers. Furthermore, the push for edge efficiency and the design of lightweight networks optimized for real-time embedded processing, alongside the integration of adversarial-aware security features, are critical for the practical deployment of dependable UWB systems. By consolidating the fragmented literature into a unified analytical framework, this study establishes a reproducible baseline that clarifies current methodological choices and provides a clear direction toward robust, efficient, and context-aware indoor positioning solutions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/electronics15010181/s1. Table S1: PRISMA 2020 Checklist.

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Abbreviations

The following abbreviations are used in this manuscript:

3GPP	3rd Generation Partnership Project
AI	Artificial Intelligence
AE	Autoencoder
ANN	Artificial Neural Network
AoA	Angle of Arrival
AR	Augmented Reality
ARM	Advanced RISC Machine
AUC	Area Under the Curve
BERT	Bidirectional Encoder Representations from Transformers
BiLSTM	Bidirectional Long Short-Term Memory
BLE	Bluetooth Low Energy
BN	Batch Normalization
CDF	Cumulative Distribution Function
CIR	Channel Impulse Response
CNN	Convolutional Neural Network
Conv	Convolutional
CPU	Central Processing Unit
DA	Domain Adaptation
DANN	Domain Adversarial Neural Network
DBN	Deep Belief Network
DL	Deep Learning
DNN	Deep Neural Network
DS-TWR	Double-Sided Two-Way Ranging
DT	Decision Tree
EC	Exclusion Criteria
EKF	Extended Kalman Filter
ESPRIT	Estimation of Signal Parameters via Rotational Invariance Techniques
ETSI	European Telecommunications Standards Institute
FC	Fully Connected
FCC	Federal Communications Commission
FCM	Fuzzy C-Means
FCN	Fully Convolutional Network
FiRa	Fine Ranging
FL	Federated Learning
FLOP	Floating-Point Operation
FP	First-Path
FPGA	Field-Programmable Gate Array
GAF	Gramian Angular Field
GAN	Generative Adversarial Network

GAT	Graph Attention Network
GBDT	Gradient Boosted Decision Tree
GBRT	Gradient Boosted Regression Trees
GCN	Graph Convolutional Network
GM	Gray Model
GMM	Gaussian Mixture Model
GNN	Graph Neural Network
GPR	Gaussian Process Regression
GPS	Global Positioning System
GRU	Gated Recurrent Unit
HQCNN	Hybrid Quantum Convolutional Neural Network
IC	Inclusion Criteria
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IMU	Inertial Measurement Unit
IoT	Internet of Things
IPS	Indoor Positioning System
IQ	In-phase and Quadrature
ISO	International Organization for Standardization
ISODATA	Iterative Self-Organizing Data Analysis Technique Algorithm
kNN	k-Nearest Neighbors
LDE	Leading-Edge Detection
LED	Light-Emitting Diode
LiDAR	Light Detection and Ranging
LightGBM	Light Gradient Boosting Machine
LoS	Line-of-Sight
LSTM	Long Short-Term Memory
LSTMs	Long Short-Term Memories
MAE	Mean Absolute Error
MaxPool	Maximum Pooling
MCU	Microcontroller Unit
MI	Magneto-Inductive
ML	Machine Learning
MLP	Multilayer Perceptron
MRQ	Main Research Question
MUSIC	Multiple Signal Classification
NLoS	Non-Line-of-Sight
PDoA	Phase Difference of Arrival
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSD	Power Spectral Density
RAM	Random Access Memory
REMNet	Residual Enhancement Multiscale Network
ResNet	Residual Network
RF	Random Forest
RIS	Reconfigurable Intelligent Surface

RMSE	Root Mean Square Error
RMS	Root Mean Square
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
RQ	Research Question
RSS	Received Signal Strength
SINR	Signal-to-Interference-plus-Noise Ratio
SLIPT	Simultaneous Lightwave Information and Power Transfer
SNR	Signal-to-Noise Ratio
STD	Standard Deviation
STS	Scrambled Timestamp Sequence
SVGP	Stochastic Variational Gaussian Process
SVM	Support Vector Machine
SVR	Support Vector Regression
TCN	Temporal Convolutional Network
TDoA	Time Difference of Arrival
TinyML	Tiny Machine Learning
TL	Transfer Learning
ToA	Time of Arrival
ToF	Time-of-Flight
TPU	Tensor Processing Unit
TWR	Two-Way Ranging
UKF	Unscented Kalman Filter
UWB	Ultra-Wideband
VAE	Variational Autoencoder
VBGMM	Variational Bayesian Gaussian Mixture Model
VLC	Visible Light Communication
VRNN	Variational Recurrent Neural Network
WLS	Weighted Least Squares
WLoS	Weak Line-of-Sight
WoS	Web of Science
XGBoost	Extreme Gradient Boosting

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