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Research Article

A Smart RFID-Driven System for Dementia Patient Tracking: A Machine Learning Approach for Monitoring and Localization

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Abstract: The global increase in the elderly population, which is expected to reach 2.1 billion by 2050, has highlighted the need for reliable monitoring systems to assist elderly individuals, especially those with dementia. More than 55 million people worldwide live with dementia, a disease liable to induce fatal incidents such as wandering off and falling, resulting in almost 30% of injury-related deaths in the elderly. Current technologies, including GPS and camera-based systems, face severe limitations in indoor environments, such as privacy intrusions, high costs, and dependence on line-of-sight visibility. This study introduces a novel, cost-effective radio frequency identification (RFID)-based tracking system optimized for indoor settings to address these gaps. Leveraging the Internet of Things (IoT) architecture and cloud computing, our solution employs battery-less RFID tags embedded in unobtrusive wearable devices (e.g., anklets or bracelets) to enable real-time, multi-individual tracking without compromising privacy or relying on external power. Our proposed system uniquely integrates the efficiency of a low-complexity, cost-effective fingerprint-based localization framework with real-time data analytics and optimized ML models to achieve the accuracy, affordability, and scalability required for smart home applications for dementia. Extensive evaluation in simulated smart home environments demonstrates a 98% localization accuracy with NN and a modified KNN algorithm, outperforming existing approaches. As a proof of concept, the developed RFID-based localization system is capable of accurately tracking multiple elderly individuals within the home setting. Overall, the proposed system showed excellent accuracy results with only off-the-shelf components. The proposed system addresses scalability and cost barriers, offering a robust alternative to the more expensive and often hard-to-use commercial systems. This developed system not only enhances the safety of patients with dementia but also establishes a robust, adaptable framework for future IoT-driven healthcare applications.

Keywords: Dementia; Internet of Things; K-Nearest Neighbor (KNN); Radio Frequency Identification (RFID); Received Signal Strength Indicator (RSSI); Smart Home

1. Introduction[1]

Recent surveys have reported that the number of elderly people older than 65 will surpass the number of newly born children by far (Chen et al., 2018). Fall is the main cause of long-term disability and injury-related mortality in the elderly population. Falls are also a major cause of traumatic brain injury in the elderly. Furthermore, falls have been one of the predominant threats to people's health, particularly in aged citizens, leading to morbidity and disability (Lau et al., 2022). Approximately $30 billion is spent annually treating the elderly because of falls.

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Most falls occur at home (Stark et al., 2021). Furthermore, falls constitute a major health concern among older adults, with more than 30% of community-lodging older adults in the United States experiencing a fall annually. This statistic highlights the huge burden of falls within the older adult population in the United States, although the prevalence of falls may vary across different countries and demographic groups (Azizan, 2024). Furthermore, the cost of a fall-related injury for an older adult is USD 30,000, and the use of IoT and Aİ for fall detection can save healthcare systems billions of dollars annually. Wearable sensors and smart home devices assisted by Aİ can collect data on movement patterns to identify risks and detect the onset of falls in real-time (Alharbi et al., 2023).

The main cause behind the recent boost in life expectancy is the drastic improvement in quality of life. Nevertheless, the growing prevalence of dementia and other age-related conditions among the elderly population brings with it serious health threats. Dementia is a disease that causes memory loss. This causes the elderly to not realize the environment surrounding them, and hence, they will become vulnerable or fragile and prone to dangerous falls (Chen et al., 2018). The prevalence of dementia is booming with an aging population and is expected to reach 152 million people worldwide by 2050. More than approximately 60% of the elderly suffering from dementia fall yearly (Taylor et al., 2021).

Dementia is a chronic disease with a serious deterioration in cognitive functions that is far different from normal behavior in the younger generation. This disease affects judgment, comprehension, thinking, and consciousness. Deterioration in the control of emotions or motivation often precedes the deterioration of cognitive functioning (Triapthi et al., 2021). This condition usually impairs judgment, insight, and thinking and consciousness faculties. Impairment within the domain of cognitive functioning is typically preceded by impairment in the modulation or instigation of emotions or drives (Triapthi et al., 2021). Among the numerous forms of dementia, Alzheimer's disease is the most common. It is a condition in which the cells in the brain undergo a gradual degenerative process.

Disorders such as Alzheimer's disease and loss of memory (amnesia) tend to develop among individuals with cognitive impairment. In recent years, major research efforts have been devoted to designing and developing systems for enhancing the quality of life, especially for the elderly. The most formal definition of quality of life (QOL) is the ability to perform daily tasks without assistance, to be active, and to have fun (Rondon-Garcia and Ramirez-Navarro, 2018). According to the World Health Organization, QoL depends on an individual's awareness of his/her place in life, considering the cultural context, value systems, personal goals, and concerns. Smart-home services, such as localization for the elderly, enhance their QoL (Rondon-Garcia and Ramirez-Navarro, 2018). Furthermore, technological advancement has led to more environmentally friendly products and services being produced. The wellbeing of our future will depend on how we can produce technology that governs our climate and health (Berawi et al., 2022). In addition, smart cities are harnessing technological and digital solutions to maximize resource efficiency and drive a sustainable environment (Berawi, 2023). Recently, the healthcare sector has been equipped with state-of-the-art wireless communication technologies. As a result of this, drastic research efforts have contributed to the huge development of intelligent systems boosting healthcare services globally (Varadharajan et al., 2018). Older people often exhibit wandering behavior due to dementia. This behavior often includes spatial randomness and aimless persistent walking (Kolakowski and Blachucki, 2019).

With the Internet of Things (IoT) and related technologies, it is now possible to localize individuals using cost-effective technologies. Recently, motion and ambient sensors have been embedded in objects to monitor the daily activities of elderly individuals with dementia. However, these technologies are costly and computationally intensive (Suzuki et al., 2018). Bluetooth low energy (BLE) anchor nodes use an extension of the Kalman filter-based approach and K-nearest neighboring method to locate patients with dementia indoors through wearable tags. However, these methods suffer from deterioration in performance in 3D setups due to challenging BLE power computation (Thakur and Han, 2021; Tabbakha et al., 2021; Kolakowski and Blachucki, 2019; Arakawa et al., 2018). In contrast, RFID is a specialized system with transponders or tags affixed to individuals or objects. These tags interact with readers through electromagnetic waves. These passive tags operate without batteries and boast both longevity and affordability. Each tag holds a distinct ID and sends it out when it comes near a specific reader. There are three types of tags: a passive type of tag is adopted, a semi-passive tag is implemented, and an active type of tag is employed (Alsinglawi et al., 2017). Passive tags do not contain memory, and hence are low cost and have a long life.

The RFID system, to a large extent passive RFID, is beneficial for energy harvesting and is a low-cost technology. Compared to the Global Positioning System (GPS) and wireless sensors, RFID saves a large amount of power. UHF passive tags communicate with the reader using electromagnetic backscatter at a range of up to 25 m depending on the antenna specifications. Localization of older persons is one of the critical applications of RFID. In addition, RFID-based positioning technologies are widely used primarily for indoor positioning techniques because the performance of GPS deteriorates indoors.

These are essential enablers for many new applications, primarily due to their significantly reduced cost (Ma et al., 2020). Figure 1 shows a typical passive RFID-based system for indoor localization.

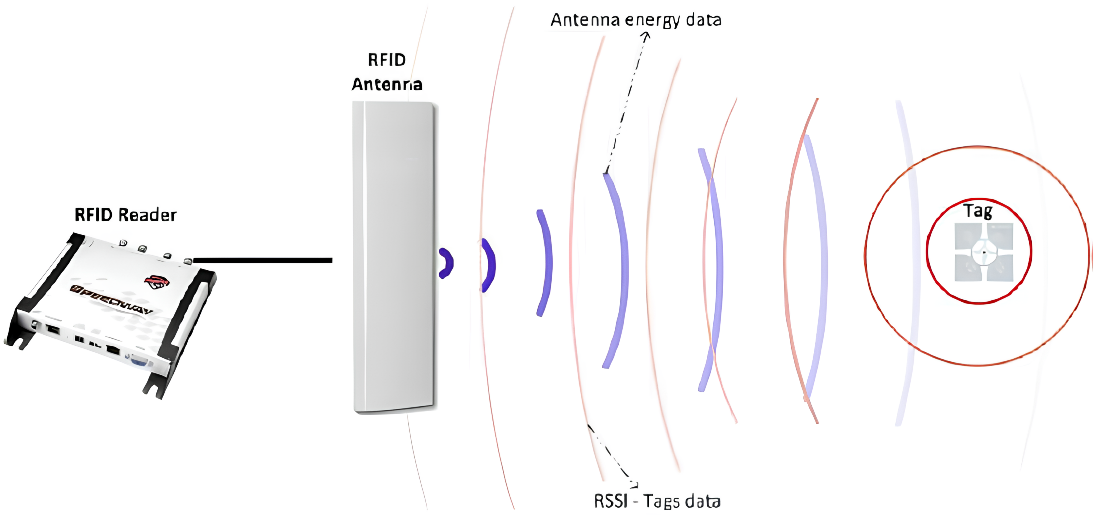


Figure 1 Typical RFID-based system for localization

Current localization methods are either active or passive. RFID tags are used in active methods, whereas passive localization methods use tracking without an electronic device. Thus, RFID is used to localize the elderly to detect their whereabouts in hazardous zones (Shit et al., 2019). Global positioning system (GPS) is used for outdoor localization. Indoor localization systems have already been widely applied mainly for providing localized information and directions. Most of them focus on commercial applications that provide information, such as advertisements, guidance, and asset tracking. Medical-oriented localization systems are also uncommon. Several researchers have utilized indoor positioning for detecting frailty of elderly (Aldelemy et al., 2024; Bibbò et al., 2022; Tegou et al., 2019). Given the fact that an individual's indoor movements can be indicative of his/her clinical status, we present a low-cost indoor localization system with high accuracy that can be used to localize elderly people suffering from dementia and frailty. This study focuses on the design of a low-cost, cost-effective system that can easily be installed in smart nursing homes and requires minimum technical skills to operate and maintain. For indoor positioning, GPS localization is degraded due to signal attenuation. Therefore, indoor localization constitutes an open research problem with many challenges (Molina et al., 2018). However, nowadays, sensor nodes embedded in smart phones can perform indoor positioning (Brena et al., 2017). These sensor nodes incorporate a barometer, accelerometer, manometer, wireless fidelity (Wi-Fi), gyroscope, RFID, and BLE sensors.

In particular, many researchers use the fingerprinting localization algorithm to obtain the signal strength index (A. Li et al., 2019). Some researchers have used the fingerprint localization algorithm along with BLE scanners to measure the similarity between extracted features (Jiang et al., 2021). Current research showed that RSSI-based methods are more favorable than other existing techniques because it is easier to collect RSSI samples using current technologies. Other positioning algorithms that use fingerprinting and RSSI include pattern matching by taking hidden patterns within the data of RSSI (Soro and Lee, 2019). Fingerprinting methods are divided into two stages: online and offline. During the offline stage, the system gathers the RSSI values of access points (APs) from different reference points and then stores them. Subsequently, the system estimates the new target point by comparing the measurement values with those stored. It is the positioning where the target point measurements bring closer to those in the mapping database. Unfortunately, RSSI suffers from multipath fading, instability, and fluctuation, which makes it difficult to achieve precise indoor positioning. Thus, several methodologies have been developed for boosting performance (Molina et al., 2018; Fu et al., 2018; X. Zhang et al., 2018). Among the proposed methods, ANNs have been suggested because of their strong capabilities in image pattern matching (Soro and Lee, 2018). Researchers reported that a drastic fluctuation of RSSI deteriorates the ANN performance. Moreover, a preprocessing step is applied on the raw RFID data, which improves the effectiveness of the algorithms. Subsequently, selected and specially configured ML algorithms are trained on the data.

The smart home of older people demonstrated in this paper employs a proximity technique to alleviate the computational complexity during the time-consuming off-line fingerprinting process, as pointed out earlier. The dense deployment of high-performance antennas has also been employed. The advantage of the fingerprinting algorithm compared to the distance-based method is that the performance of the fingerprinting algorithm is less affected by multipath propagation radio signal, in addition to the fact that the fingerprinting technique does not require simultaneous detection of at least three access points. The proposed research is an extension of some previous work published at the SSD Conference (Raad, Deriche, and Kanoun, 2021).

The main contributions of the paper are as follows:

(1) Design, implementation, and testing of a multi-person localization system for the elderly suffering from dementia in a smart home setup

(2) Implementation and testing of a suite of machine learning algorithms that support the developed prototype with accurate localization performance.

(3) A scalable, intelligent monitoring framework that combines optimized ML algorithms with passive RFID technology. Unlike existing systems, the proposed prototype eliminates the need for costly infrastructure, leveraging battery-less tags for effortless deployment in residential settings.

(4) Implementation and testing of a proof-of-concept prototype with off-the-shelf components. The proposed system leverages IoT RFID-based technology with machine learning algorithms.

The remainder of this paper is structured as follows: Section 2 covers the related work, Next, the proposed framework is discussed in Section 3. Section 4 presents the experimental results and a discussion of the results. The conclusion of the article is given in Section 5.

2. Related Work

Recently, wearables have advanced drastically. Among the advantages of wearable electronics are wearability and adaptability to the human body (ergonomics, material, weight, and adjustable size); continuous and relative ease of use (no need to turn off the device); safety; and autonomy (setting up user preferences). Recently, several researchers have discussed IoT-based wearable biosensors for monitoring patients' illness without human involvement (Chin et al., 2022). In addition, the advancement of the Internet of Things (IoT) technology and other forms of remote systems, such as telemedicine, have also allowed healthcare professionals to monitor patients remotely, which is helpful for patients with mobility difficulties or who live in rural areas (Naeim et al., 2023).

Currently available wireless technologies for indoor localization include infrared, ultrasonic, WLAN, ultra-wideband (UWB), Bluetooth, ZigBee, and RFID. A distinctive feature of a WSN is that it consists of many sensors with limited energy availability and is often used over long distances. Sensor nodes have sensing, processing, and communication components in addition to storage capabilities (Hendrarini et al., 2022). One of the popular positioning systems based on infrared is Active Badge. Active badge technology is used for the localization of people in an indoor environment. This technology consists of minute battery-operated wearable devices, where each room and door have an infrared transceiver to communicate with the badge for localization. Although infrared indoor positioning systems offer high precision, they rely heavily on line-of-sight and short-range transmission, which significantly limits their practical applications. The ultrasonic solution performs well in specific systems, such as the Active Bat and Cricket (C. Zhang et al., 2020). However, given the attenuation in transmission and the huge deployment costs, widespread application is challenging. To determine the wireless terminal's location, WLAN localization systems, such as Wi-Fi localization, employ TOA, TDOA, or RSSI methods. Researchers here proposed indoor localization techniques using sparsely deployed Wi-Fi APS (H. Zhang et al., 2020).

Although the Wi-Fi localization can be easily deployed, the target only needs to be a wireless terminal with, but it is not preferred for scenarios with limited energy requirements, and the related infrastructure adds extra cost. Ultra-wideband (UWB) technology sends data through brief, powerful pulses. Some researchers have suggested combining hardware and data fusion techniques that integrate both UWB and IMU for indoor localization and motion detection for better results (H. Zhang et al., 2020). Other researchers proposed techniques for indoor positioning that were based on a wireless network of ultrasound sensors in the context of ambient intelligence (Andò et al., 2021). UWB can provide localization at the level of centimeters, but it is much more expensive to build. ZigBee is a short-range technology, low power but much of interest among researchers. Although it can achieve communication between nodes in a self-organizing network, the ZigBee network must be established beforehand and is power hungry (Feng et al., 2018). RFID is used for localization with a majority of four techniques: RSSI, TOA, TDOA, and AOA (Fang, 2018). RFID is a very appropriate technology for positioning in the context of IoT because of its small size, exceptionally dependable identification method, and low cost.

However, the localization using RFID is subjected to some interference, and multipath fading in passive RFID systems within indoor environments can disrupt signals (Luo et al., 2017). (Amin and Deriche, 2016; Bouchard et al., 2014) addressed the issue of indoor localization using elliptical trilateration and fuzzy logic. Nowadays, indoor localization is essential, particularly for detecting incidents such as elderly elopement or falls caused by dementia. However, it is worth noting that researchers discussed several challenges of IoT systems. For example, signals can experience interference, reflection, and multipath fading, reducing the accuracy of indoor positioning. Other researchers used RSSI and power level for locating RFID tags, thus reducing the need for additional hardware and mitigating the overlap between antennas (Dharani-Tejaswini and Balasubramanian, 2018).

Recently, the elderly have accepted RFID for enhancing their well-being and care in the healthcare setting because the tags are designed to be comfortably worn by elderly individuals and can provide highly accurate positions of the elderly (Raad et al., 2018). Within the healthcare sector, the caregivers utilized RFID technology to bridge the disparity in healthcare advancement and enhance elderly care and wellbeing. RFID-based systems have dramatic added value in smart home healthcare, as follows: 1) the RFID tags are compact in size and are easy to integrate into a human body; 2) they could be worn by the elderly, relatively unobtrusive, and lightweight. Today, with the availability of a plethora of advanced wireless sensors and a significant surge in technology complexity, pinpointing the location of objects or individuals in real time through Real Time Location Systems (RTLS). This is typically achieved through the use of tiny, wearable nano-electronic devices (or tags) attached to things or people. RTLS is the integration of software and hardware used to accurately trace and receive the actual position of people, assets, or anything of high value to an accuracy that is very high.

Table 1 presents a summary of the comparison of indoor positioning techniques based on Wi-Fi, UWB, and passive RFID technologies. As shown in Table 1, a tradeoff exists among those techniques. In addition, based on our research on similar systems, we decided to use battery-less passive RFID technology. Such a solution is very economical for our specific application of interest and very easy at the same time. More importantly, the proposed RFID-based solution will be very easy to use, not requiring network connectivity as opposed to using other protocols, such as the ZigBee protocol, which is extremely complex. The proposed RFID solution outperforms the GPS-based solutions within an indoor setting. Recently, some researchers have proposed an extensive review of indoor positioning techniques highlighting the main challenges. They showed how ML techniques, both supervised and unsupervised, can be used for the fusion of positioning techniques to produce a comprehensive indoor positioning system (Nessa et al., 2020).

Furthermore, other researchers have extensively explored machine learning and deep learning techniques to detect elderly people's activities. Ma et al., 2020 developed a human activity framework based on random forest, K-NN, SVM, and artificial neural network (ANN) techniques. Moreover, Cheng et al., 2020 combined three-dimensional relative positioning and absolute positioning techniques based on deep learning and user RSSI, phase, and timestamp of tags to obtain a better positioning stability of the localization technique. However, deep learning approaches have proven to be inappropriate because they are highly computational and costly, particularly when only low-power computing resources, such as RFID technology, are available. To the best of the authors' knowledge, only a few researchers have discussed the hybrid scenario of combining RFID technology with ML algorithms to address the problem of localizing frail elderly at home, particularly in a smart home environment. In addition, the adaptation of ML-based solutions for indoor localization is still in its infancy (Shahbazian et al., 2023; Merenda et al., 2022; Muangprathub et al., 2021; Nessa et al., 2020). Hence, the purpose of this research is to use state-of-the-art advancements in RFID and machine learning for the localization of frail elderly suffering from dementia in a smart home setting. Furthermore, the global market for iot-based fall detection systems is expected to reach USD 4.5 billion by 2025 (Alharbi et al., 2023). Our current research is based on our previously published research on realizing an RFID-based smart home for the elderly suffering from Alzheimer's disease (Wasim-Raed et al., 2023).

Table 1 Comparative Mapping of Indoor Localization Technologies and Their Suitability for Elderly Monitoring in Healthcare Environments (H. Zhang et al., 2020)

Method	Technology	Accuracy	Pros	Cons
WiFi (Luo et al., 2017)	RSSI fingerprinting	1-2 m	Low cost simple system	Requires database for fingerprinting, loweraccuracy
UWB (Minne et al., 2019)	ToA/TDoA/AoA	0.1-1m	High accuracy, simple system	Short range, battery-operated
RFID (S. Li et al., 2020; Buffi et al., 2018)	RSSI	Varies	Low power, low cost, user-friendly, good for indoor and outdoor use	Limited to one tag perlocation

A comparative mapping of indoor localization techniques, including Wi-Fi- and UWB-based methods, is discussed in Table 1 to provide insight into existing work. Here, certain factors that largely control application-based system selection, such as localization accuracy, infrastructure cost, energy requirements, and deployability in real-world healthcare scenarios, are contrasted against each other. The map shows that UWB techniques rank higher in accuracy but rank lowest on power and cost constraints for affordable home-care solutions, whereas passive RFID-based solutions are practically implementable at the price domain. This provides a strong argument for selecting simple passive RFID that offers practical accuracy to room-level tracking of elderly individuals across diverse situations, such as nursing homes or private homes.

3. The Proposed RFID-Driven Tracking System

In general, older adults have various special needs to live a normal life. They require support to enhance independent living and maintain autonomy in activities of daily living. In addition, older adults may require compensatory assistance to address functional limitations and maintain independence in performing basic functions. These need necessitate the development of care models and support services using state-of-the-art technologies (Rybenská et al., 2024). Furthermore, elderly people with chronic diseases, such as dementia, and living alone at home are generally too weak and cannot perform basic life activities. In addition, the elderly who suffer from dementia often display psychotic abnormal behavior and may be subject to instances of total unawareness, which entails continuous support and assistance. Necessary services and facilities for the elderly to enjoy their life will be available in a smart home. An important feature of a smart home is an unhampered smart positioning system. The main benefit of this approach is that it can precisely determine the whereabouts of aged people at the level of rooms with a high degree of accuracy. Surveillance technologies like cameras now achieve these. These work fine, but they intrude on privacy.

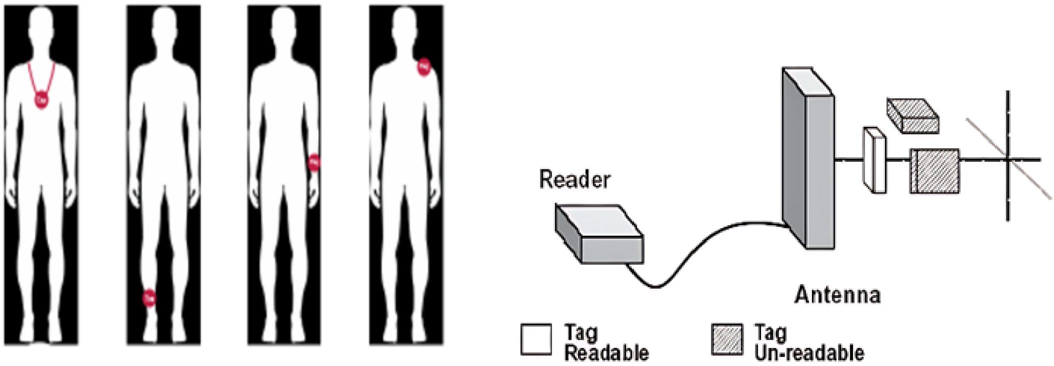
We used one Sirit UHF RFID robust reader, which is frequently utilized in industrial settings, for this study. The reader used in this study captures tags in the coverage area of the distributed antennas. The reader is connected to four circularly polarized UHF antennas; it operates with a horizontal 3 dB beamwidth of 66° and a vertical 3 dB beamwidth. The antenna has an RF power of 30 dBm with an operational range of 7–15 m. It works over the frequency range of 865–868 MHz. The Sirit RFID reader can sample 10–50 tags per second at an RF power of 30 dBm. With a typical home environment setup and a large enough number of zones (say around 20), such sampling is high enough to detect the movement of the elderly across the different zones within the home.

Notably, in our proposed system, the number of readers is not defined per square meter but rather based on zone-level coverage and line-of-sight considerations tailored to indoor environments. Typically, one RFID reader with multiple directional antennas (e.g., 2 to 4 antennas per reader) is sufficient to cover a large functional area ranging from 50-100 square meters (which is applicable to our scenario), depending on the layout and interference factors. Therefore, the deployment unit is per zone, not per square meter. The RFID scenario description and data collection are briefly described in the next subsections. Then, the implemented ML algorithms are discussed in more detail.

While localization based on fingerprinting has been extensively studied in the literature, the novelty we bring here is the way we adapt and deploy the technique for a scalable, low-cost smart home environment focusing on elderly care. The system uses off-the-shelf RFID equipment and does not require Wi-Fi or Bluetooth or any calibration steps; hence, it can be deployed in smart homes, schools, and nursing homes without requiring any technical skills. Furthermore, the method sets real-world constraints to be tested experimentally on layout placement and signal orientation, which are usually almost never addressed in their entirety in previous works.

3.1 RFID Deployment and Data Collection under Different Scenarios

Passive RFID tags were used to locate the patients in this study. Therefore, each patient wears a tag. The literature has shown that the ideal placement of the RFID tag for monitoring the movement and wandering of elderly individuals depends on balancing several factors, including accuracy, comfort, privacy, shadowing problems, and practicality. Typical tag placements include: Wrist, Ankle, Shoe, Chest, Waistband, etc. (see Figure 2 (a)). We ran several experiments to determine the best tag placement. The experiments were carried out for more than 10 min for each placement, and the results showed comparable performance across the different positions, except for the shoulders' placement, which resulted in low accuracy due to high signal interference from the different antennas. For a detailed analysis of optimal tag placement, we recommend the recent work by Comai et al., 2025 (Table 2).



(a) (b)

Figure 2 (a) Tag positioned on the body, (b) Tag orientation angles with respect to the reader.

Table 2 Localization accuracy for various tag position scenarios

Tag Placement	Correct Detection Rate
Necklace	99.6%
Anklet	91.2%
Bracelet	97.8%
On Shoulder	66.9%

We also conducted several tests to analyze the effects of tag orientation with respect to the reader's antenna. Figure 2 (b) shows the extreme positions of the tags (in terms of orientation) with respect to the antenna of the Sirit reader. We also present our results in terms of the tag detection probability as a function of the angle between a sample tag and the reader's antenna (Table 3). The probability was averaged over 10 possible readings, and the orientations were changed between 0° and 90° (perpendicular position) in increments of 10°. The results show that the detection probability is acceptable for deviation angles of up to 60°. The results in Tables 3 and 4 are extracted from various experiments conducted in the RFID Lab.

In this work, the proposed system was developed for a simple setup-up scenario consisting of a room with an external exit antenna placed at the exit of the house to detect if the patient leaves the house Figure 3(a). Figure 3(b) displays the real-world extension of the proposed system over a typical smart home. Based on this setup, we developed the workflow shown in Figure 4, which summarizes the localization flow diagram. Moreover, the lab where the tests were conducted is assumed to be divided into hypothetical squares, with each square representing a particular zone, such as a room or a bathroom inside the house (Figure 5). Figure 5(a) illustrates a case in which the patient is in a zone that is considered away from the door, while Figure 5(b) illustrates the case in which the patient is very close to the door and an action needs to be taken. The main reason for considering the case in Figure 5(b) is to prevent dangerous wandering (elopement) of the elderly in a zone close to the door as this can lead to fall or fracture due to cognitive decline. Hence, immediate action, such as alarming the carer or closing the door (automatically), should be taken when necessary.

In addition, a localization feature on the zone level is added to the proposed solution. This indicates whether the elderly people are inside the house or wandering outside the house, triggering an alarm. In summary, the main scope of the research within this existing proposal is as follows: Localizing the elderly suffering from dementia at the room level and not where they are in the room.

Table 3 Effects of orientation angle on tag detection probability

Orientation angle	Detected tags	Probability of detection
0°	10/10	1
10°	9/10	0.9
20°	8/10	0.8
30°	9/10	0.9
40°	10/10	1
50°	10/10	1
60°	8/10	0.8
70°	7/10	0.7
80°	1/10	0.1
90°	0/10	0

Now that disruptive technology is available, it has become possible to localize anybody or anything in real-time. Developing Real-Time Location Systems (RTLS) makes this possible by using tags attached to objects or people at any time. With an RTLS, one can track and localize assets and people by associating a minute wireless device (or tag) with each person. RTLS at choke point detects the location of an object or person (at entry or exit point) such as a gate.

For our proof of concept, we used the University RFID lab as a testbed for a standard smart home with the aim of monitoring the elderly's whereabouts and triggering the onset of fall or an emergency when there is a need. The setup uses four antennas spread across the lab area's corners. The system can detect whether a given tag is inside or outside a specific zone by monitoring a tag at a particular choke point (such as exit doors). In a typical smart home setup, as seen in Figure 3(a), the RFID readers are strategically installed within rooms and at entry points to monitor the movements of elderly individuals, particularly for detecting wandering behaviors and movement between rooms or at critical "choke points." The system also sends alerts when a person is detected near an exit (such as a doorway), helping to prevent unsafe outside wandering.

We conducted a series of experiments by varying the number of RFID readers, antennas, and—most importantly—the number of spatial zones defined within the monitored smart home environment to ensure reliable monitoring and enhance localization accuracy. For a typical 200 m^2 residential layout, our findings (supported by the literature) showed that deploying 3–4 RFID readers in conjunction with approximately 6–7 antennas provides good coverage. However, in our experimental laboratory setup—covering an area of approximately 50–60 m^2—we achieved good performance using only one RFID reader connected to four antennas. Given that our tracking task was reframed as a classification problem, the monitored space was discretized into square zones. Starting with some zones (3x3), the granularity was gradually increased until optimal classification accuracy was attained. The experimental results revealed that the optimal configuration consisted of 20 zones arranged in a 4×5 grid. Consequently, each square zone covered approximately 2.5 m^2, corresponding to dimensions of about 1.6×1.6 meters. This spatial granularity was instrumental in determining the effective RFID tag resolution for our setup. RFID tag resolution is commonly defined as the smallest physical distance or area in which a system can reliably distinguish the presence or movement of a tag. Higher resolution (e.g., 0.5 m) yields more precise localization, whereas lower resolution (e.g., 2 m) provides only coarse estimates (e.g., room-level detection). Based on our experimental configuration, the effective tag resolution was approximately 1.6 × 1.6 meters, offering a balanced trade-off between localization precision and system complexity for typical smart home applications.

Finally, the proposed prototype is designed to use off-the-shelf components. In particular, assuming an average-sized house of 200 m2 , we will need around 4-5 readers and about 8-10 antennas. This brings the average cost of hardware (including accessories) to about 2, 000−2,500. Such a cost is considered to be affordable for most families with elderly people living with them. For those with lower income, we expect that nursing homes can easily bear the cost of about 10, 000−15,000 in total, covering around 20-25 rooms and adjoining halls, bathrooms, etc. Because each reader supports multiple antennas and passive tags are battery-free, the cost and system overhead grow linearly with the area, confirming the scalability of the proposed system.

To address scalability, the system was designed modular: a zone-based architecture. Each zone corresponds to one small spatial unit of approximately 2.5 m2 (in our prototype), and the number of zones may be increased proportionally to the floor area. Since the localization task is described as a classification problem over zones, increasing the number of zones does not significantly increase the model's complexity. In addition, the system uses passive RFID tags, which are inexpensive and battery-less, thus allowing high-scale implementations for tracking multiple individuals in a large facility.

(a) (b)

Figure 3 (a) Home control device Antenna setup at the exit, (b) Sample smart home RFID deployment

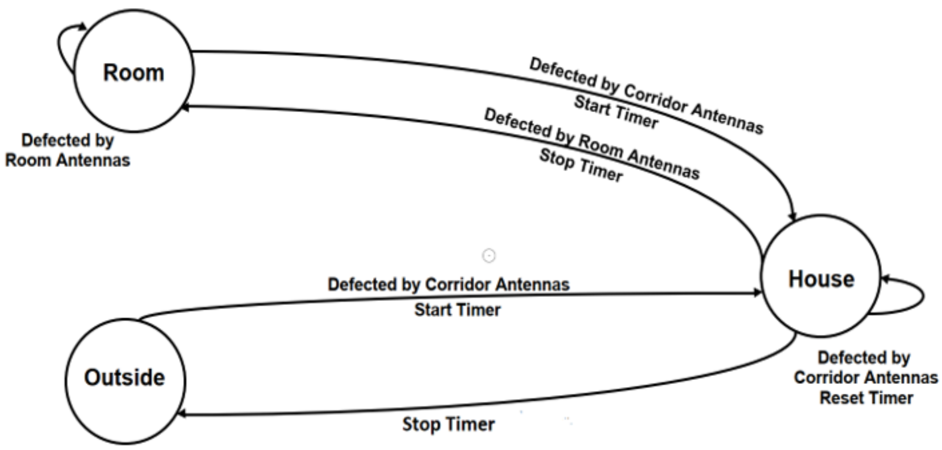
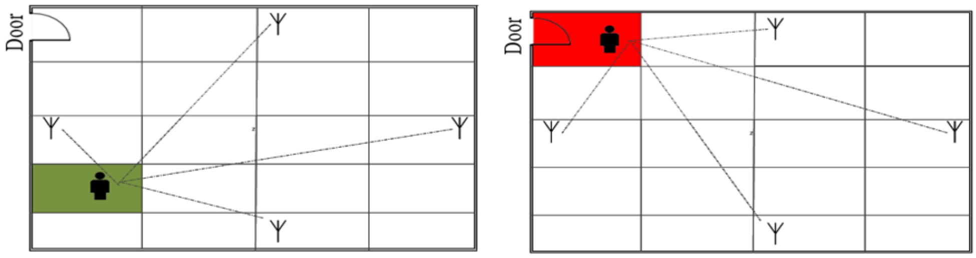


Figure 4 The Proposed Elderly Localization Workflow

The developed setup was tested with volunteers acting as three elderly people. The collected data are the RSSI and the phase angle corresponding to each location using the fingerprint algorithm. The RSSI and phase angle data were collected on the spot using a Nordic mobile RFID reader. Note that indoor location measurements usually suffer from attenuation and shadowing due to the normal presence of different stutterers. Hence, several readings were taken at each zone corresponding to one class. The number of readings is not even because the antenna connectivity for some zones was better than that for others. Therefore, the collected data are not balanced. Also, some antennas enjoyed overall better coverage than others. Repetitions are used for classes that have missing data inputs at the respective places to compensate for the data imbalance. The collected data were stored in a database and formatted to be used as a dataset for the implementation of the ML algorithms.

Furthermore, the system was tested for different furniture and obstacle arrangements and tag orientations to simulate real-world uncertainties associated with room conditions. The results show that the proposed system consistently performs, maintaining an accuracy rate of above 90% in room-level detection even when subjected to moderate signal interference or environmental changes. This indicates a robust and highly appropriate system for monitoring the elderly at home.



(a) (b)

Figure 5 (a) Scenario with patient far from the exit door. (b) Scenario with patient close to exit door

3.2 System Testing and Discussion

Several tests were conducted to determine the optimal transmit power of the RFID reader. The results are summarized in Table 4. The table shows that the best detection probability in our setup (around 70 cm between the reader and the first seat, shaded numbers) is achieved when the transmit power is set to around 24 dBm.

Table 4 Localization accuracy for various tag position scenarios

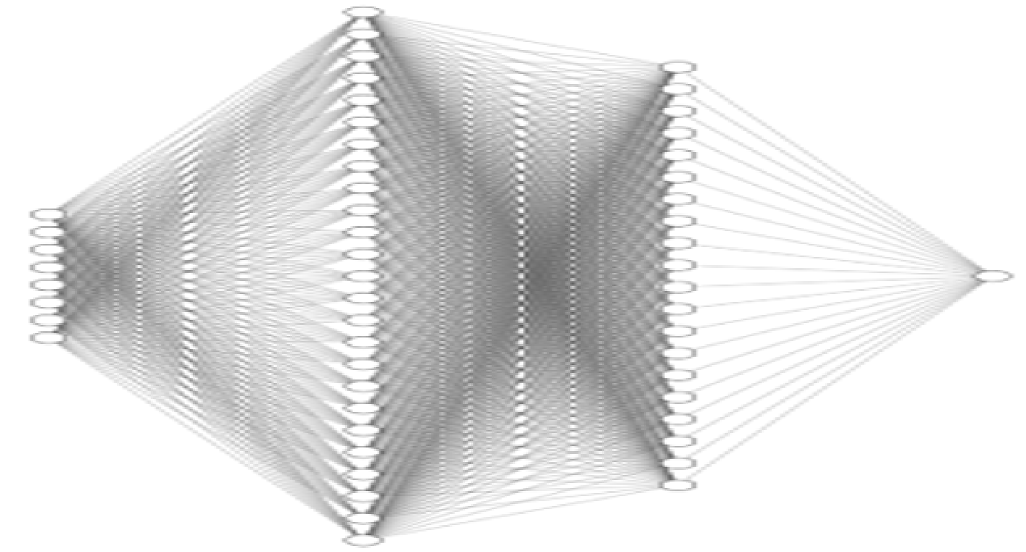
Power (dBm)	Probability of detection / meter						
	.2m	.3m	.4m	.5m	.6m	.7m	.8m
21	.90	.82	.78	.76	.69	.62	.60
24	.90	.85	.83	.80	.75	.72	.67
27	.91	.83	.84	.81	.77	.74	.69

To determine the optimal RF power of the Sirit Reader for our application, we changed the power setup between the minimum transmit power of 10 dBm and the maximum power of 30 dBm. The testes were performed in increments of 5 dBm. There were some cases of missed detection for all setups, except when the transmit power was set to 25-30 dBm. Based on these experiments, we configured the Sirit reader to operate at a maximum transmit power of 30 dBm (Raad, Deriche, and Sheltami, 2021).

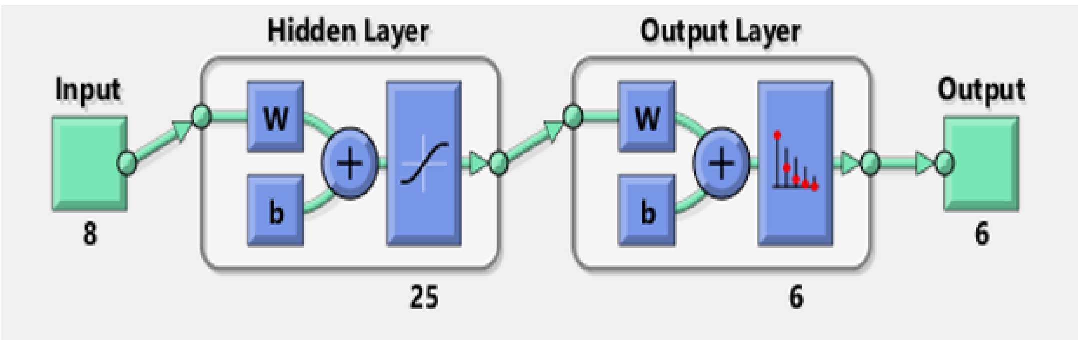
3.3 Localization Using Machine Learning

To test the proposed framework, we selected two conventional classifiers, namely, a neural network classifier and a KNN classifier. Here, the NN used comprises three layers: an input layer, a hidden layer, and an output layer (Figure 6(a)). Each layer consists of several neurons (Alvarez-Narciandi et al., 2019; Møller, 1993). After extensive simulations and trials, a hidden layer of 25 neurons was selected for our neural network. The last layer in the neural network where the desired predictions are obtained is the output layer. For our setup, we are considering twenty (20) classes ($4\times$ 5 grid covering the whole area).

Figure 6(b) shows the NN workflow, where the output of the hidden layer is activated using a sigmoid logistic function, $s(t) = \frac{1}{1+e^{-t}}$. The training was achieved using the scaled conjugate gradient backpropagation algorithm.



(a)



(b)

Figure 6 (a) NN architecture and (b) parameter training layout

To avoid this classification bias and keep simplicity in mind, we also implemented and tested the system with a KNN classification. The algorithm is an iterative approach based on classifying new cases and improving performance using a given distance metric. It is another supervised ML algorithm that uses iterative solutions to improve classification accuracy (Du et al., 2020; Won et al., 2018). The Euclidean distance is the most common distance metric, where the new data point is classified based on the nearest K-neighbors of the new data point. Several forms of KNN exist, e.g., weighted KNN, subspace KNN, and fine KNN. The weighted KNN assigns different weights to the 10 nearest neighbors based on their proximity to the new point. The subspace KNN uses a random set from the neighbors for all features at each iteration. The classifier makes detailed distinctions between different classes and considers only 1 neighbor.

System Training, Validation, and Testing: The features used in this study correspond to the RSSI and phase values received by each antenna. Because there are four antennas, eight features are obtained. The dataset is split into three sets: training, validation, and testing to prevent overfitting of training data. This helps the model to be generalized and able to predict new samples not seen before.

Feature normalization: The features needed to be normalized and properly scaled before training the model. This is because the RSSI and phase values have different scales, and processing them in absolute terms can be confusing to the classifier and may result in some features having more weight than others. Therefore, the features were normalized by calculating the mean of each feature and subtracting it from the dataset value, then finding the SD of each feature, and dividing the dataset values by the standard deviation: $X_{\text{normalized}} = \frac{(x-\mu)}{\sigma}$, where μ and σ represent the mean and SD values for each featured vector, respectively. After normalizing and preprocessing all the features, the results are presented to the classifier.

These models were selected for their noise resistance. The high classification accuracy observed in many trials (up to 98% with four antennas) demonstrates the system's ability to withstand minor fluctuations in received signal strength and phase, which is typical in indoor scenarios.

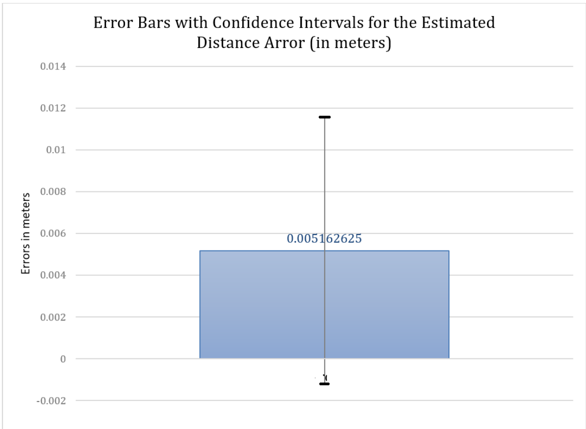
4. Results and Discussion

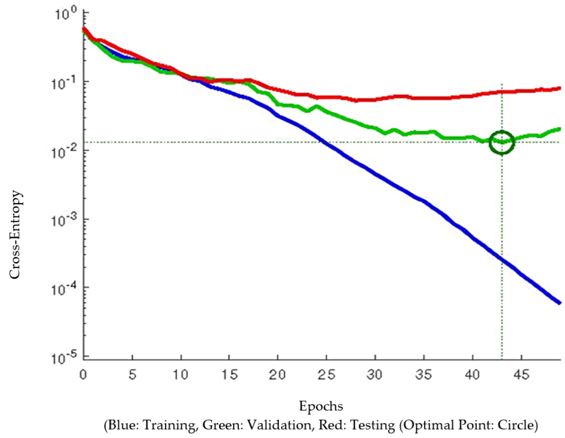
This section discusses the accuracy of the ML algorithms implemented for patient location and tracking in the scenario described in Section 3. The data collected through the RFID system consisted of RSSI and phase values. These are defined as features of the ML algorithm. The data collected over hours of patient tracking are presented to the ML algorithms as follows: 70% for training, 15% for validation, and 15% for testing. This division is changed later to study the effects of different combinations.

4.1 The Neural Network Classifier

The difference between the predicted values and the target values (real patient location) can be visualized in the error histogram after training a feedforward neural network (Figure 7 (a)), where 20 bins are used. Each bin has a width of 0.0947, and its occurrence frequency is expressed in its corresponding height. Figure 7 (b) shows the performance of the ML algorithm as the cross-entropy vs epochs. Cross-entropy measures the similarity between the output predicted by the neural network (representing the location of the elderly) and the true label retrieved from the training, validation, or test data (obtained from the offline fingerprinting process). It represents a loss function, and the curve tends to decrease as the accuracy of the predictions increases. As shown in Figure 7(b), the best performance of cross-validation is obtained when its curve is at its minimum, i.e., 0.013 at epoch 43. This helps in generalizing the model and preventing overfitting.

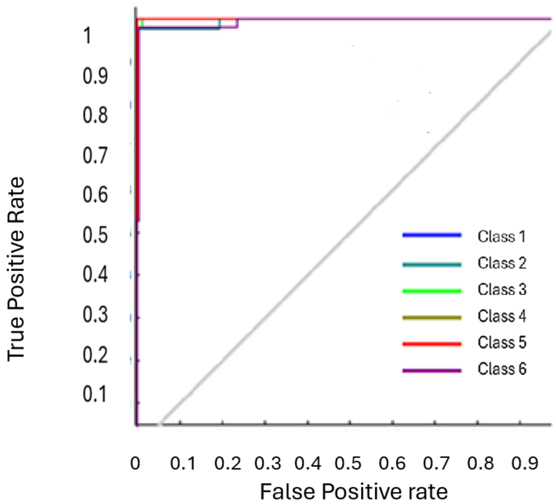
Figure 8 (a) shows the ROC curve for six selected classes (regions spread across the area). Outputs from the neural network relate to localization zones of the elderly within the home. The ROC curve plots the true positive rate as a function of the false positive rate, where the former is identical to the classifier's sensitivity, and the latter is represented as 1 - specificity. The area under the curve (AUC) is commonly used to measure the quality of the classifier; an AUC value of 0.5 implies a random classifier, whereas a value of 1 indicates a perfect classifier. It appears that all classes perform well compared with the straight line representing the random classifier. Additionally, in Figure 8 (b), the gradient plotted against the number of epochs depicts how the neural network is being trained. The number of failed validations for each epoch is plotted versus epochs. The gradient is found to be 71×10^{-5} at epoch 50, and the validation checks are 6 at epoch 50.

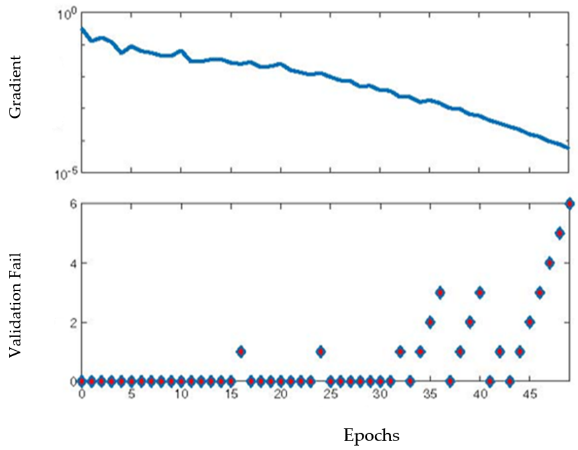




(a) (b)

Figure 7 (a) Error Histogram for NN, (b) Cross entropy vs epochs for training, validating, and testing the NN





(a) (b)

Figure 8 (a) ROC Curve, (b) Training States

4.2 Effects of Features and Antennas

Table 5 shows the effect of using the RSSI and phase angle values taken from one, two, three, and four antennas. A comparative analysis is performed using the methods described earlier. Specifically, we consider 3 cases: the NN, the subspace KNN with cross-validation (S-KNN1), and the subspace KNN with holdout validation (S-KNN2). When using only one antenna for classification, a lower accuracy is achieved. However, as expected, the accuracy is enhanced when more antennas are used. This is due to the suppression of residual noise when more features are added. Hence, employing several antennas in the localization and classification tasks is recommended. A random classifier is expected to result in an accuracy of (100%)/6 = 16.7%, and in the results obtained in this work, we far exceed this baseline even with only one antenna.

We note that good performance is achieved when at least 3 antennas are used. This result is consistent with the triangulation concept. Similarly, we note that the subspace KNN performs better than the NN because the KNN efficiently uses the features presented to the network. We have conducted several experiments to investigate the effect of body shadowing on placing wearable tags on different parts of the body. Placing the tag on the necklace resulted in the best performance because the necklace tag is more stable on the body and has excellent orientation with respect to the antennas. Moreover, the use of multiple features (predictors) provides more flexibility to the ML algorithms by constructing a higher-dimensional fitting function (Wang and Zheng, 2013). Different methods of validation were used to combat and account for overfitting, and the results obtained in this work show a satisfactory amount of generality to new data. Time is the last time the readings were recorded. These are updated in real time, but the system displays only the final readings from the antennas. As shown in Table 5, the KNN also obtained the best performance of 98% using 4 antennas. Alharbi et al., 2023 supported this result, reporting that KNN achieved the highest accuracy of 98% in RFID tag detection.

Table 6 shows an example of different time stamps of indoor elderly localization in real-time. This information is of utmost relevance for sending prompt alerts to the caregiver through the cloud at the onset of the elderly roaming outside the house, in conjunction with Figure 4, which clearly shows the zone-based elderly localization workflow. Furthermore, the universal RFID protocol: EPC class1 gen2 ISO 18000, used in our proposed solution is applicable in various areas, such as asset tracking and other areas, and is easily scalable and integrateable in larger systems with little overhead and zero calibration. In addition, the RFID reader we used is Java-enabled and can be easily connected to the cloud.

Finally, at the backend, a program (written in Python) triggers an alarm in case the elderly person leaves the room for more than 3 minutes, considering the slower pace of movement. At this time, the elderly would have passed the antenna in the corridor and would no longer be detected.

Table 5 Effects of number of features (classification accuracy)

No.Antennas	No.Features	NN	S-KNN1	S-KNN2
1	2	50.6%	29.9%	26%
2	4	72%	90%	83%
3	6	87.3%	95%	93%
4	**8**	**97.2%**	**98%**	**98%**

To position our system within the recent literature, we compared its performance with those reported for similar RFID-based indoor localization and fall detection systems. Alharbi et al., 2023 conducted a comprehensive performance evaluation of several classifiers for RFID-enabled smart carpet fall detection. Their results demonstrate that most of the classifiers (e.g., GRU: 41.37%, RF: 42.75%, XGB: 48.42%) resulted in a moderate level of accuracy, whereas the KNN performed considerably better with an accuracy of 99.97% and recall and precision approaching perfection.

Our system is an indoor localization system that can facilitate smaller than room-level localization with 98% accuracy with multiple antennas and cheap infrastructure. In addition, while both systems rely on RFID and KNN-based classifications, our contribution lies in proposing a generalizable zone-based localization framework that focuses on scalability, cost, and ease of deployment in an elderly-monitoring setting; hence, it does not require activity-specific training. In a way, KNN showed continuously reliable performance in all kinds of RFID-based application areas, implying lightweight machine learning in smart elderly care.

Notably, the results discussed in the paper by Alharbi et al., 2023 showed that KNN outperformed neural network-based classifiers, such as the gated recurrent unit (GRU). The KNN performance is largely due to the nature of the dataset, which accounts for the RFID tags' spatial activation patterns. KNN works well with structured and well-separated feature spaces because it is a distance-based, non-parametric method. On the other hand, neural networks are meant to model patterns; hence, they become less effective here given the small dataset size, and they require heavy training and parameter tuning. Therefore, for RFID-based spatial recognition assignments with clean class separation, KNN attains better accuracy with lower complexity than neural networks.

While the scenarios and experimental setups mentioned in the paper are different from ours, we show below a table comparing the performance of our proposed systems to the results discussed in the paper for the sake of completeness.

Table 6 Location of elderly with timestamp

ID	Location	Time
0X00A1	In House	11:44:29
0X00A2	Roaming outside House	11:44:01
0X00A3	Inside Room	11:44:38

Table 7 Performance of Different Classifiers

Classifier	Accuracy	Recall	Precision	F1-Score
NN-GRU	41.3	0.41	0.23	0.26
XGB	48.4	0.48	0.33	0.36
LR	41.8	0.41	0.17	0.24
KNN	99.7	0.99	0.99	0.99
GB	48.9	0.49	0.17	0.39
RF	42.7	0.42	0.48	0.26
RFID-ML (ours)	98.2	0.97	0.98	0.975

5. Conclusions

In this study, we developed a low-cost, battery-less, machine learning-based RFID system for the real-time localization of multiple elderly individuals in a smart home environment. The proposed system was successfully tested in a university setup using proximity-based indoor localization combined with fingerprinting techniques. Machine learning algorithms, including KNN and Neural Networks, were applied to achieve excellent localization accuracy, with the KNN achieving 98% accuracy. System reliability is expected to improve even further with additional antennas, especially in detecting wanderings near exit points, hence providing timely alerts to remote caregivers. Future work will focus on upgrading the proposed system for broader use in a multi-floor home nursing environment for the elderly suffering from dementia, optimizing it with passive RFID tags, and mitigating body shadowing effects. By enabling timely caregiver alerts and supporting early intervention strategies, this study contributes a critical step toward safer and more autonomous living for vulnerable populations. The framework's adaptable, battery-less architecture and machine learning foundations extend its utility to diverse healthcare applications beyond smart homes, including clinical patient monitoring, hospital asset tracking, and institutional emergency response systems. Although the system is not aimed at substituting clinical-grade localization solutions in emergency setups, it surely provides a dependable room-level tracking solution. The design is robust and flexible in different room layouts, showing practical reliability in caregiver monitoring and alerting system for early warnings. Unlike most academic prototypes, this system has been deliberately made inexpensive and simple, with deployment flexibility as a first-order concern. This practical component of our design distinguishes it and adds new insight to the deployment of effective AI-driven localization in aging-in-place and dementia-care settings. The scalability of the system has also been validated through practical modeling and cost analysis. Its modular architecture, zone-based ML design, and passive RFID infrastructure make it well-suited for deployment in larger smart homes or institutional care settings.

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Author Contributions

Conceptualization, proposed framework and developing the methodology for writing the original work were led by Raed. and Deriche; Deriche also supervised the algorithm implementation, data analysis, results, validation, investigation, resources, data curation and original draft preparation. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare that there is no conflit of interest.

Declaration of AI

We confirm that we have not used any generative AI tools in the preparation of this paper

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