LoRa-based IoT Platform for Monitoring Dementia Patients' Wandering Behaviour

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Declaration

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Mohamed Ashfak Date: 2025-04-27

This is to certify that this dissertation is based on the work of Mohamed Yoosuf Izzath, Shinthujen Inpagaran, and Mohamed Ashfak under my supervision. The thesis has been prepared according to the format stipulated and is of acceptable standard.

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Abstract

Dementia is a syndrome significantly impacting the daily lives of individuals, predominantly among the elderly population. It leads to a deterioration in cognitive capabilities, encompassing memory, concentration, reaction time, problem-solving abilities, and difficulties in language articulation and word recall. Due to the impairments in spatial awareness, memory deficits, restlessness, and agitation commonly observed in individuals with dementia, there is a significant propensity for these patients to wander. Wandering behavior in dementia patients is a critical issue, as it can lead to disorientation, exposure to hazardous environments, and difficulties in returning home. Various types of wandering behaviors have been identified, such as aimless wandering, pacing, lapping, and shadowing. These behaviors can be triggered by anxiety, confusion, unmet needs, or an attempt to find a familiar location or person. Managing wandering behavior requires continuous supervision, which places a substantial burden on caregivers. To address this issue, This study mainly focuses on developing a wearable IoT (Internet of Things) device equipped with LoRa modules for real-time tracking and intelligent monitoring of dementia wandering patients. LoRa technology supports the development of low-energy, long-range Internet of Things (IoT) devices, and LoRa modules serve as essential components in our IoT platforms, facilitating the transmission of sensory data to central applications and enhancing remote monitoring capabilities. The wearable device is being developed with a cost-effective approach, primarily aimed at middle and low-income countries with high dementia prevalence and prohibitive healthcare costs. Designed for energy efficiency, these devices minimize the need for frequent charging, thereby ensuring consistent operation and improving practicality for dementia patients who may be prone to forgetting to recharge. The proposed IoT platform provides continuous location monitoring, ensuring timely intervention by caregivers to prevent potential dangers. Continuous data on patient movement collected via wearable devices is transmitted to the cloud for machine learning, trajectory analysis, and anomaly detection to identify wandering scenarios. The IoT platform is engineered to integrate multiple wearable devices and sensors, forming a comprehensive medical suite for dementia patients. The integration of wearable devices allows the pre-processing of movement data on the device, reducing network latency and optimizing response times for critical alerts. The web application is designed with an intuitive user interface and incorporates features such as caregiver alerts, multi-user sup-

port, and historical tracking data visualization. A smart detection strategy is suggested in order to guarantee that wearable technology is utilized regularly and to offer dementia patients efficient monitoring. In order to detect when the wearable is no longer in contact with the body, it combines sensors like bioimpedance, capacitive touch, and inertial measurement unit (IMU). This enables the system to react instantly, assisting caregivers in maintaining trustworthy supervision by either sending alarms or initiating other required actions. Given the sensitivity of patient location data, the system integrates end-to-end encryption added in the LoRa module and secure cloud storage to safeguard user privacy. Designed for middle and low-income countries, the solution prioritizes affordability by leveraging cost-effective hardware and open-source technologies. The device enhances patient safety, promotes independent living, and reduces the risks associated with wandering behavior in dementia patients. The design and development of the proposed IoT platform focused on user-centric design and design science research methodology. This research has the potential to improve the quality of life for individuals with dementia and simplify the responsibilities of family members, caregivers, and healthcare providers.

1 The introduction

Dementia is a syndrome that significantly impacts the daily lives of individuals, predominantly among the elderly population. It leads to a deterioration in cognitive capabilities, encompassing memory, concentration, reaction time, and problem-solving abilities, as well as difficulties in language articulation and word recall (McKhann et al., 1984). Dementia shows long symptoms, and it is crucial to identify dementia in its early stages and provide necessary aid. Following is an illustration that shows the different stages of dementia.

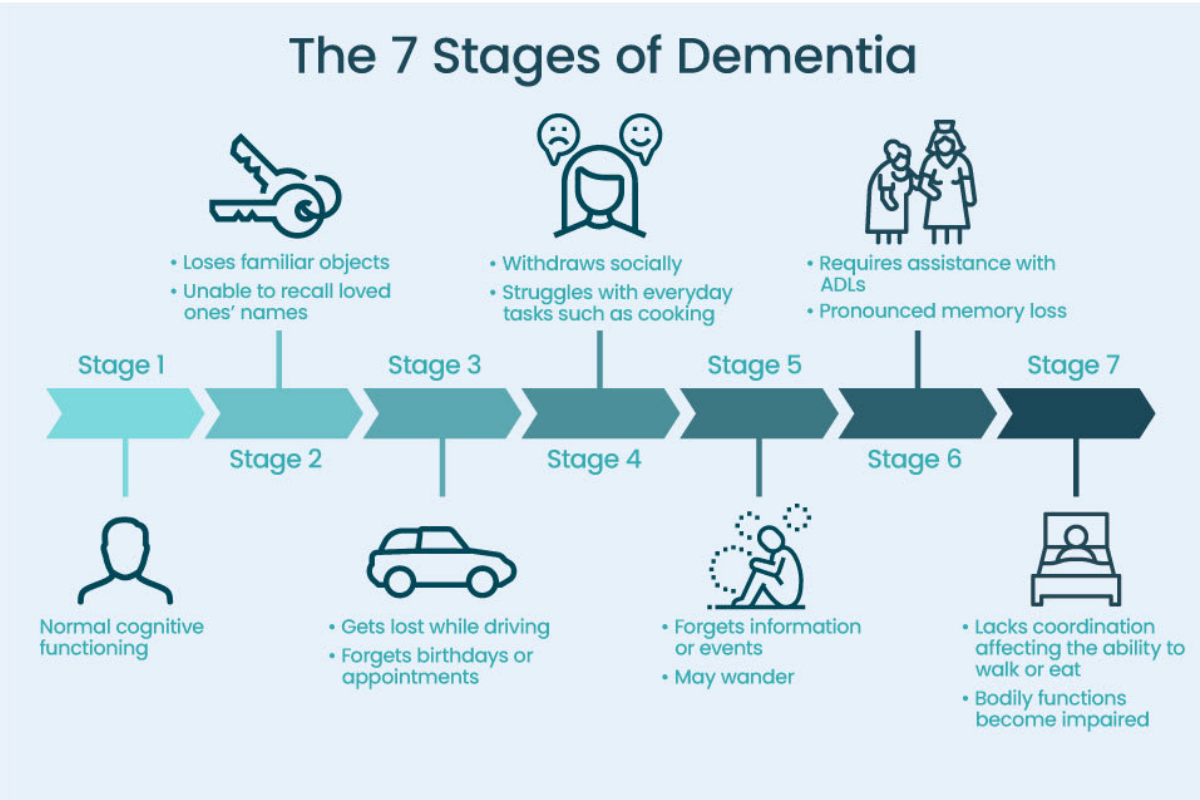

Figure 1: Stages of dementia (JasmineHEH, 2024)

Individuals with Alzheimer's disease or other forms of dementia may lose the ability to recognize familiar places and faces, leading them to wander and become disoriented. This behavior can occur at any stage of the disease and poses significant safety concerns. Approximately 60% of those living with dementia will wander at least once, with many doing so repeatedly. People with dementia who wander often show several signs, such as trying to go "home" even when they're already there, forgetting familiar locations, or taking an unusually long time to walk from one place to another (*Wandering — Alzheimer's As-*

sociation 2024). Tracking and monitoring the location of dementia patients is important in both indoor and outdoor situations due to safety issues. Many devices are available for monitoring the location of dementia patients, but most are very expensive and not accessible in middle and low-income countries where dementia cases are more prevalent. LoRa is one of the communication protocols that provides long-range communication in an energy-efficient and cost-effective way. This research project focuses on developing a cost-effective, energy-efficient, intelligent tracking system based on LoRa technology for dementia patients, which provides real-time monitoring facilities for caregivers. In addition to hardware efficiency, this work also introduces a machine learning-based dynamic geofencing approach to improve safety through adaptive zone classification based on patient movement behavior.

1.1 Research Background

According to the literature review, most dementia tracking systems implement static geofencing, which involves a set of coordinates tracked by GPS. However, many patients in the middle stages of dementia are still capable of performing daily activities, even though they may occasionally forget their location.

Static geofencing systems are often rigid and fail to adapt to the patient's daily movement patterns or environmental factors. In diverse geographic regions such as Sri Lanka, where conditions can vary from urban to rural, a fixed set of coordinates may not accurately represent safe or risky areas. This limitation can lead to either missed alerts or false alarms, reducing the effectiveness of caregiver intervention. To address these shortcomings, recent studies suggest the potential of dynamic geofencing, where zone boundaries adapt based on behavior and context.

When we consider wearable devices for dementia patients these devices usually lack the means to confirm continuous contact with the body, resulting in gaps in monitoring. This is particularly very important in dementia care, as patients may accidentally remove or misplace wearables. Skin contact is detected by capacitive touch sensors resistance changes across skin tissues are measured by bioimpedance sensors and movement patterns are analyzed by IMU sensors. Real-time off-body scenario identification is made dependable by the combination of these technologies. In the literature, most studies have focused on cellular communication as a medium for communicating between devices, with only a limited number of studies exploring real-time tracking using LoRa technology. Given that LoRa enables long-range communication and is energy-efficient, developing a wearable device that utilizes LoRa could be a cost-effective solution for middle/low income countries, providing an affordable alternative to expensive devices.

1.2 Project Aim and Objectives

1.2.1 Project Aim

To develop a cost-effective, energy-efficient, and intelligent real-time tracking system including off-body device detection for dementia patients using LoRa communication, integrated with a machine learning-based dynamic geofencing approach to enhance patient safety and support caregivers through adaptive zone classification and predictive wandering detection.

1.2.2 Project Objectives

- To design and develop a real-time location tracking system for dementia patients using LoRa technology, with a wearable IoT device (LoRa end) and a home IoT device (LoRa gateway), and a protocol that is scalable for multiple home devices.
- To implement a dynamic machine learning model that classifies patient movement into adaptive safety zones (Safe, Warning, Danger) based on GPS data and contextual features such as terrain and movement patterns.
- Make sure a wearable device stays on a dementia patient's body by efficiently alerting caregivers in real-time when it is taken off, allowing the patient to benefit fully from ongoing support and monitoring.

1.3 Research Questions

- How to develop a cost-effective and energy-efficient real-time patient tracking system using LoRa with a wearable device?
- How effectively can a machine learning-based dynamic geofencing system classify patient zones using real-time GPS data and contextual movement patterns to support early detection of wandering behavior in dementia patients?

- What ways can multiple sensors be combined to accurately detect when a wearable device is removed from a dementia patient's body?

1.4 Justification of Software Engineering Project

This project introduces a real-time dementia monitoring platform that uses IoT devices communicating via the LoRa medium. We have developed a wearable device that is energy-efficient, cost-effective, and user-friendly. Additionally, a web application has been created to facilitate easy real-time monitoring of dementia patients.

Current dementia tracking systems predominantly rely on static geofencing techniques, which are unable to adapt to the changing behaviors and needs of dementia patients. These systems use predefined boundaries to trigger alerts, often resulting in false alarms or missed events as they fail to account for patient movement patterns and environmental factors.

This project introduces a novel approach by integrating machine learning (ML) for dynamic geofencing. Unlike static geofencing, this system uses real-time GPS data and contextual factors, such as movement history and terrain details, to dynamically classify areas as Safe, Warning, or Danger. The use of machine learning allows the system to learn from patient behavior, improving its ability to predict wandering patterns and offer timely alerts. This dynamic approach ensures that geofences are personalized and responsive to the individual needs of each patient, enhancing both the effectiveness and accuracy of monitoring.

Additionally, the incorporation of shapefiles for spatial data processing is an innovative aspect of this project. Shapefiles, which contain geographical features such as land use, roads, and terrain, enable the system to classify zones with a higher degree of precision. This combination of machine learning and spatial data allows for a more nuanced understanding of the environment surrounding dementia patients, creating safer and more efficient geofencing boundaries. The dynamic classification of zones based on both movement data and environmental context represents a significant advancement over traditional, static geofencing methods.

Maintaining the wearable gadget on the body is very important to the system's overall dependability. By avoiding erroneous data gathering and guaranteeing prompt interventions, the integration of numerous sensors for off-body detection directly helps this objective. This element improves system integrity and user safety, particularly in-patient groups with memory impairments.

1.5 Research Methodology

The research project employs design science research (DSR) as its methodology, providing a systematic approach to developing practical, user-focused solutions aimed at enhancing the quality of life for people with dementia and assisting their caregivers. By engaging in an iterative process of design, development, and evaluation, DSR ensures that technology effectively and sustainably meets the genuine challenges faced in dementia care, while also taking into account the intricate and evolving needs of both patients and their caregivers (Brocke, Hevner, and Maedche, 2020).

The protoype monitoring system includes two IoT devices: wearable LoRa devices that will be attached to dementia patients and a home device that is placed in the patient's house. Wearable devices periodically send GPS location and sensory data, while nearby home devices capture this data and transmit it to the web application. Since the patient can walk beyond the range of one home device to another, a routing protocol was developed to provide balance and scalability in the LoRa network. A web application was developed to provide remote, real-time monitoring of dementia patients. The application contains profiles for each patient and their caregivers, facilitating user-friendly monitoring of dementia patient.

The dynamic geofencing artifact that uses machine learning to classify areas as Safe, Warning, or Danger based on real-time GPS trajectories and contextual spatial data extracted from shapefiles. The methodology involves: identifying the problem of static geofencing limitations, defining the objectives of a dynamic and adaptive solution, designing and developing a predictive LSTM-based model, demonstrating its functionality through test scenarios with GPS datasets, evaluating its accuracy using metrics such as Mean Squared Error (MSE), and communicating the findings. Integrating shapefile data (e.g., terrain, roads, and land use) with movement history is a novel aspect of this approach, enabling geofences to be continuously refined based on both behavioral and environmental cues.

The implementation of a strong off-body detection feature effectively addresses a significant issue. By integrating capacitive touch sensing, motion tracking, and biometric verification, the system guarantees ongoing confirmation that the device remains in contact with the patient. This capability not only boosts the safety and dependability of the system but also enhances the confidence of caregivers. Being aware that the device will automatically alert them if it is taken off or malfunctioning allows caregivers to grant dementia patients greater independence and mobility. This creates a more compassionate caregiving atmosphere, alleviates the stress of constant supervision, and enables caregivers to have trust in the technology being used.

2 Literature Review

2.1 LoRa based IoT Applications

LoRa (Long Range) is a technology used to enable connectivity between IoT devices over long distances while being energy efficient. LoRa, created by SEMTECH, employs spread spectrum modulation derived from chirp spread spectrum (CSS) technology. This enables long-distance signal transmission that is less sensitive to interference, requires less energy in the modules, and enhances communication between transmitters and receivers (*LoRa PHY — semtech.com* 2025).SIGFOX, NB-IoT, and LTE-M are alternative technologies designed to enable long-distance communication among IoT devices. The comparison between these solutions and LoRa can be found in the Table 1.

LoRaWAN (Long Range Wide Area Network) is a communication protocol and system architecture for long-range, low-power communications used primarily in Internet of Things (IoT) applications. It is built on top of the LoRa (Long Range) physical layer, which employs Chirp Spread Spectrum (CSS) modulation to enable long-range transmission with low power consumption. LoRaWAN defines the communication protocol and system architecture for the network, including device-to-gateway communication, security, and network scalability. LoRaWAN operates in unlicensed ISM (Industrial, Scientific, and Medical) bands—typically 433 MHz, 868 MHz, or 915 MHz—depending on the region. It supports three classes of end devices (A, B, and C) to balance latency, power consumption, and downlink availability (Figure 2). Due to its ability to support large-scale deployments, long-range communication (up to 15 km in rural areas), and battery life of up to 10 years, LoRaWAN is widely used in applications such as smart cities, agriculture, environmental monitoring, and industrial automation. LoRaWAN is governed by the LoRa Alliance, a nonprofit association of member companies collaborating to drive the global success of the protocol as an open standard for secure, carrier-grade IoT LPWAN connectivity (*lora-alliance.org* 2025, Centenaro et al., 2016).

Parameter	LoRa	SIGFOX	NB-IoT	LTE-M
Technology	Proprietary (PHY), Open (MAC)	Proprietary	Open LTE	Open LTE
Spectrum	Unlicensed	Licensed	Licensed	Licensed
Frequency Band	Sub-GHz ISM	Sub-GHz ISM	Cellular band	Cellular band
Modulation	CSS	D-BPSK	2-BPSK, 2-QPSK	BPSK, QPSK, 16QAM, 64QAM
Duty Cycle / Tx Restriction	1%	140 msg/day	–	–
Frequency	433, 868, 915 MHz	868, 915 MHz	700–2100 MHz	700–2600 MHz
Bandwidth (BW)	125, 250, 500 kHz	100, 600 Hz	200 kHz	1.4 MHz
Coverage	1–10 km	10–40 km	15 km	11 km
Battery Life	10 years	10 years	10 years	10 years
Deployment	Multi-operator, self deployment	–	In-band, Guard Band, Standalone	In-Band LTE
Standard	LoRaWAN	No	3GPP Release 13	3GPP Release 12
Security	AES-128	AES-128	LTE security	LTE security

Table 1: A comparison of the long-range communication technologies (Jouhari et al., 2023)

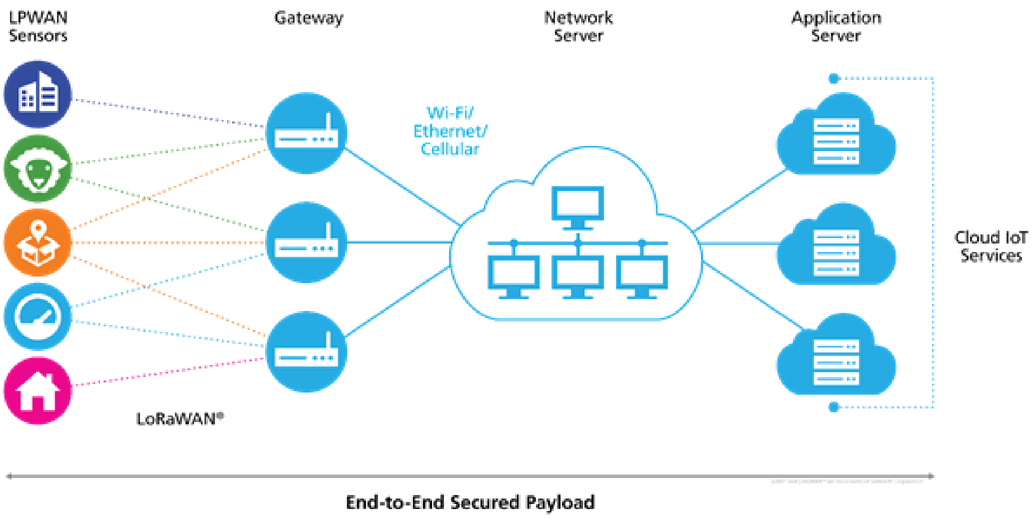

Figure 2: LoRaWAN Architecture

LoRa is utilized across various sectors such as agriculture, smart buildings, smart cities, and industrial projects, among others. LoRa technology is particularly advantageous for agricultural applications due to its impressive connectivity range. The study Chanwattanapong et al., 2021 presents a LoRa network designed for agricultural applications, enabling real-time environmental monitoring through multi-wireless sensor nodes that collect data on soil moisture, temperature, humidity, and light intensity. The LoRa gateway facilitates long-range communication between the sensor nodes and cloud storage, allowing for efficient data transfer and analysis every 15 seconds. This system enhances agricultural practices by providing accurate environmental data, which can lead to better decision-making and resource management for farmers (Chanwattanapong et al., 2021).

Figure 3: LoRa network for agriculture Chanwattanapong et al., 2021

The Rachmani and Zulkifli, 2018 paper presents a monitoring system for starfruit plantations utilizing LoRa technology, which allows for data transmission over distances of up to 700 meters, ensuring effective communication within the farming area. The system integrates various sensors, including pH and soil moisture sensors, to collect critical agricultural data, which is then processed by an Arduino UNO microcontroller. Data is periodically sent to a cloud database, enabling farmers to access real-time information through a user-friendly interface available on both desktop and mobile platforms. The implementation of this system aims to enhance agricultural practices by providing insights into soil conditions, thereby assisting farmers in making informed decisions regarding irrigation and fertilization.

Smart cities are a common domain where LoRa technology is widely used to develop advanced applications. The paper Rao and Chaudhari, 2020 introduces a LoRaWAN-based traffic clearance system aimed at facilitating the swift passage of emergency vehicles (EMVs) through traffic signals by creating a green corridor. LoRa technology is utilized for its long-range, low-power communication capabilities, allowing EMVs to transmit their unique ID and GPS coordinates to nearby traffic signals. This system enables traffic signals to change to green automatically when an EMV approaches, thereby minimizing delays and improving response times during emergencies. By leveraging the strengths of LoRa, the proposed solution addresses existing challenges in traffic management, such as energy efficiency and complexity, while ensuring reliable communication and real-time monitoring (Rao and Chaudhari, 2020).

2.2 LoRa-based Tracking Systems

LoRa can be utilized to transmit GPS coordinates from IoT devices, which can be applied for tracking individuals, vehicles, logistics, and more. In the study Torres et al., 2021, LoRa is utilized as the core communication technology in a secure IoT tracking system designed for the BIRA bicycle project (Figure 4). The architecture incorporates GPS-equipped bicycles that transmit location, route, speed, and battery data through the IPVC's LoRaWAN network to a central application server, enabling real-time monitoring and analysis. This setup uses low-cost TTGO T-Beam boards and ensures secure data transmission via LoRaWAN's built-in features like mutual authentication, data integrity, and payload confidentiality (Figure 5). The system's implementation not only supports sustainable mobility but also addresses scalability, energy efficiency, and privacy concerns across a university campus or even a city-wide scale (Torres et al., 2021).

Figure 4: LoRa Tracking device on BIRA bicycle (Torres et al., 2021)

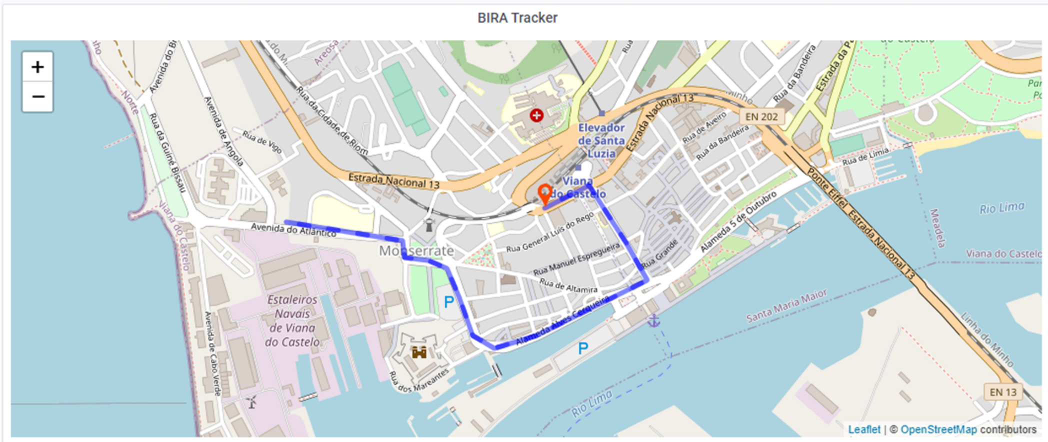

Figure 5: Application for monitor BIRA bicycle (Torres et al., 2021)

In the study Hayati and Suryanegara, 2017, LoRa is employed as the core communication technology to enable real-time location tracking of patients via wearable devices. The system architecture consists of LoRa end-devices with GPS and microcontrollers, which transmit data to LoRa gateways located in hospitals and public spaces. These gateways forward the information to local or cloud servers using Wi-Fi or mobile networks, making it accessible to caregivers and psychiatrists through a mobile application. LoRa's long-range capability, low power consumption, and scalability make it ideal for wide-area patient monitoring and emergency response support. The study Ahmed et al., 2024 utilizes LoRaWAN to create a geofencing system for remote monitoring of vulnerable communities, addressing the limitations of cellular networks in areas with poor coverage (Figure 6). The system employs an optimized Echo protocol over a mesh network to enhance reliability and scalability. LoRaWAN's long-range, low-power capabilities are crucial for monitoring subjects like cattle or patients in remote areas. The architecture includes LoRa nodes and hubs for data collection and transmission, enabling real-time tracking and geofencing alerts (Ahmed et al., 2024).

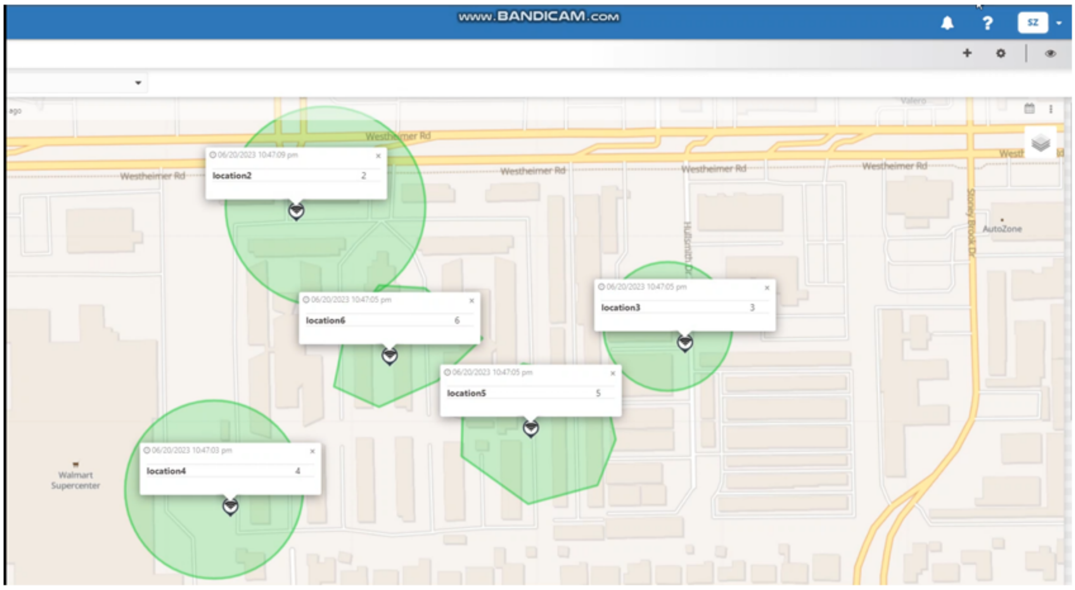

Figure 6: LoRa-based geo fencing application for vulnerable communities(Ahmed et al., 2024)

2.3 Wandering Behavior in Dementia

Wandering is one of the most challenging and hazardous behavioral symptoms displayed by individuals living with dementia, especially between those who are diagnosed with Alzheimer's disease. This behavior can be defined by aimless, tedious, or disoriented movement and may include actions like pacing, lapping, retracing the routes, or unexpectedly leaving from familiar environments. Even though these sudden movements look random to the spectators, these actions are motivated by internal psychological or cognitive conditions like perplexity, anxiety or as an effort to recollect the missed routines. According to researchers, wandering can be divided into three main categories such as patterned wandering, which explains repetitive tracing along an identical path; random wandering, which lacks a clear direction or a goal; and purposeful wandering, in which the person seems to have a destination but often guided by conditions like confusion or misbeliefs. These subcategories help to understand the level of risk and the appropriate protective measures like environmental modifications or identification aids which can help to guarantee the safety and well-being of the patient Algase et al., 2010.

A significant number of people with dementia are affected by wandering. According to studies; it is estimated that up to 60% of patients will experience wandering at least once, and often repeatedly during the illness. The outcomes of such behavior can be dire, including physical harm, exposure to dangerous conditions; even death if the person is missing for over 24 hours. *Wandering — Alzheimer's Association* 2024 highlights that the probability of getting a severe injury or death worsens the longer the individual stays missing. These situations place a heavy emotional and mental burden to caregivers, who often worry about the safety of their loved ones. As a result, most of the caregivers turn to restrictive tactics like locking out the doors or using other physical barriers or restrictions which can diminish the dignity and the quality of life of the individuals who are affected. Wandering should not be viewed solely as a symptom of a mental decline. It's just more than that. It can also be a way for the individuals to express their unaddressed needs like hunger, isolation or physical discomfort. Factors such as environmental cues, daily routines or practices from their earlier life stages also can trigger the wandering behavior. For example, some may believe that they have to "go to work" or "see a relative", even when these activities are no longer a part of their current reality. Understanding these deep motivations is the key for developing practical interventions. With the advancements in sensor-based and GPS technologies, researchers are increasingly exploring smart systems powered by machine learning to spot early indicators of wandering and take swift action. These systems are designed not just to enhance the safety, but to support the dementia patients' autonomy and dignity.

2.4 The Role of Machine Learning in Behavioral Prediction

As a core component of artificial intelligence, machine learning equips systems with the ability to learn independently from data and accurate decisions or forecasts without specifically being instructed for every case. In dementia care, particularly for anticipating and monitoring wandering behaviors, ML shows a great potential. ML is capable of processing and interpreting complex patterns over time in areas including movement, surroundings and behavioral signals. By analyzing inputs like GPS signals, accelerometer readings and mobility history; machine learning models can detect early changes in behavior and generate alerts before the situation becomes dangerous.

In the field of dementia care, supervised learning approaches are widely used to classify patient behavioral pattern changes based on pre-labeled data sets. Algorithms like Decision Trees, Random Forests, Support Vector Machines (SVM), and Multilayer Perceptrons (MLPs) have proven the effectivity in recognizing activities by analyzing data points such as GPS coordinates, timestamps, speed and direction of movement. For example, if a patient who typically walks 10 minutes in a safe familiar environment, but suddenly veers off track or heads into unknown territory, these algorithms can detect the irregularity and trigger alerts. Despite the effectiveness of the supervised models, a major drawback is their dependence on labeled data, which is both resource intensive and time-consuming to gather in medical environments. To address these drawbacks of supervised learning, researchers have turned to unsupervised learning techniques. Algorithms such as k-means, DBSCAN, Isolation Forest, and Autoencoders are used to uncover patterns or to detect unusual behaviors in dataset that lack predefined labels. These scenarios are especially beneficial in practical settings where labeling the patient is not feasible. For instance, anomaly detection systems can monitor patient behavior and flag the deviations that could be a signal of wandering or potentially hideous movement.

Deep learning techniques have recently pushed the boundaries of behavior prediction systems. Temporal models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks excel at analyzing sequential movement data, allowing for accurate forecasts of future locations and behavior trends based on prior movement history. These models are adept at capturing temporal relationships in data like speed variations, frequent pauses, and repeated paths which can be a signal of cognitive decline or anxiety-related wandering. When these systems are enriched with additional context such as time of the day, weather, patient's medical background and terrain, Long Short-Term Memory (LSTM) can generate highly detailed and more personalized predictions about wandering risks Khaertdinov, Semerci, and Asteriadis, 2021.

Recent studies are highly investigating hybrid machine learning models that bring together different modeling techniques. For example, ensemble methods or architectures that merge Convolutional Neural Networks (CNNs) for spatial data analysis with LSTM networks for interpreting time-based patterns have proven effective in fields such as elderly care and activity tracking. Moreover, reinforcement learning is gaining researchers attention for its continuous refinement with the inputs from caregivers or system feedback. This adaptive approach helps to tailor more precisely and accurate alerting while reducing the rate of false, unnecessary alerts Oliveira et al., 2022.

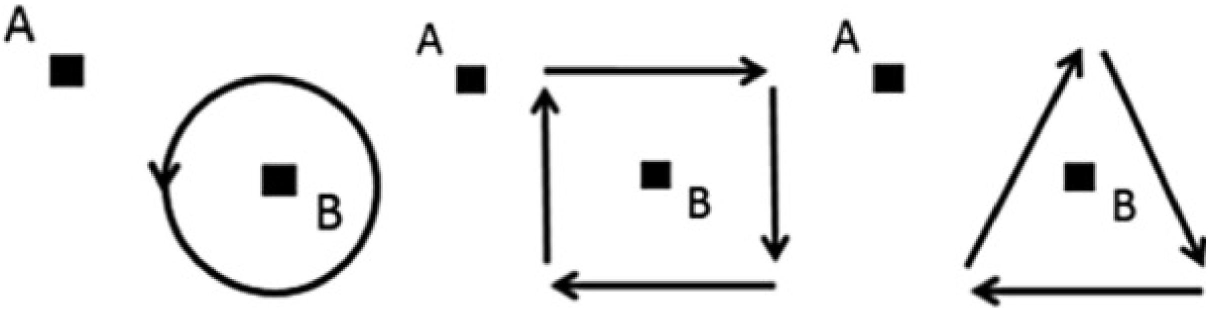

Figure 7: Wandering Patterns Oliveira et al., 2022

The combination of ML and Internet of Things (IoT) devices significantly boosts the real-time effectiveness of predictive technologies. Through the inputs from wearable devices such as GPS trackers and sensors, ML systems can process either local devices or through cloud computing. This immediacy is vital in critical care situations where timely alerts can prevent severe injuries or fatalities Jafarpournaser, Delavar, and Noroozian, 2023. Furthermore, the scalability property of cloud based models make it possible for widespread implementation across residential and institutional environments - supporting large-scaled monitoring and preventive care Sarita et al., 2024. However, there still persist some notable challenges. Concerns about patient data privacy, transparency of model, and how well the system can accommodate shifts depending on patient behavioral changes still remains. Additionally ethical concerns also arise regarding the use of constant digital monitoring and algorithm driven decision making. These should be addressed carefully. Even so, the future of ML in dementia care is still promising with the advancement of research supporting its ability to forecast wandering and provide intelligent, safety enhancing interventions.

2.5 Machine Learning Models for Wandering Detection and Prediction

Research literature has applied a wide range of machine learning models to identify and predict wandering nature in individuals with dementia. This is done by spanning from straightforward rule based methods to sophisticated deep learning algorithms. These approaches commonly rely on analyzing mobility data such as GPS paths, accelerometer readings and contextual factors to pinpoint abnormalities in movement patterns that could indicate potentially dangerous wandering scenarios Mohammed, Fakhrudeen, and Alani, 2024.

2.5.1 Rule-Based vs. Learning-Based Systems

Initial efforts to monitor wandering relied on fixed rule based systems which trigger the alerts when specific conditions like patient stays beyond a set of distance away from familiar residence environment or staying outside a defined safe zone for too long. One such approach was implemented by Nasution and Emmanuel using motion detectors and proximity thresholds. Although these systems were easy to implement, they lacked flexibility to adapt to changes in behavior over time. In contrast, learning based models provide more adaptive and personalized methods by using historical data to model typical behaviors. For example, researchers utilized an LSTM model trained on sequence of movement data to detect wandering episodes by spotting deviations of typical walking habits of individuals, which led to higher accuracy and fewer false alarms .

Approach	Rule-based	ML-based
Sub-Goal	To recognize parent-child relations based on event attributes.	
Operation	Rule generation, rule-based identification	Feature extraction, train & test
Model	Empirically derived rules	Automatic generated
Labeled Data	No	Yes (for training)
Manual Effort	Needed for generating rules	Minimal
Major Cost	Rule tuning by human	Pairing operation
Flexibility	Low (cannot recognizes beyond rules)	High (can adapt to subtle cases)

Figure 8: Comparision between rule based learning based approaches Zhang et al., 2016

2.5.2 Sequence Models: LSTM and GRU

LSTM and GRU models; both are types of Recurrent neural network (RNN) architectures widely used for analyzing time dependent data due to their strength in capturing temporal relationships. This makes these models particularly useful in the field of dementia care; especially when wandering behavior tends to involve gradual shifts in movement over time. LSTM models have been successfully added to GPS tracking data to classify time intervals to differentiate between typical mobility and wandering behaviors. These models demonstrate strong potential to understand the behavioral trends with accuracy over 85%. GRUs, which are a more lightweight version of LSTM, have offered similar functionality with fewer computational demands making them well suited for limited power usage devices like wearable.

2.5.3 Hybrid Approaches

Hybrid approaches that use different data streams and machine learning techniques tend to be more resilient and responsive. A notable example involves combining GPS and motion sensor data with a blend of Decision Trees, and Hidden Markov Models (HMMs) allowing for real time detection of wandering and forecasting of probable destination of individuals. This dual capability allows caregivers to take action before risk escalates. Additionally some other researches have integrated deep learning for feature recognition with probabilistic forecasting models. These models are capable of handling both current detection and future movement prediction in a single cohesive setup.

Our research supports the hybrid model concept by integrating dynamic geospatial features through adaptive geofencing. Instead of relying on rigid, manually defined geographic boundaries, our system employs detailed shape files to build flexible zones rich with real world features such as infrastructure, terrain and land use. These geofenced zones are labeled as safe, intermediate or high risk. They adapt over time in response to the individual's behavior, environmental context and potential hazards. By drawing on datasets from resources like OpenStreetMap and official geographic databases, and applying spatial analytics like joins and geometric computations, the system can factor in elements like road proximity, water bodies and population density to shape risk aware mobility patterns.

After classifying the labeled zones, machine learning algorithms are employed to forecast movements across these zones. For instance, of a patient begins shifting from a pre labeled safe zone to an intermediate zone, while simultaneously exhibiting a rise in walking speed and randomness of movement, the model may forecast a probable transition into a dangerous zone This allows to trigger early alerts. LSTM models are ideal for these scenarios as they consider both present location and overall trajectory. To enhance interpretability, layers of attention mechanisms further refine the model by recognizing influential temporal factors like evening hours or known risk associated with specific routes.

2.6 Feature Engineering and Context Awareness

The success of wandering detection systems depends on choosing and crafting the right features. In dementia monitoring these features are typically categorized as spatial, temporal, or contextual. Dwell time is a key spatial metric which indicates how long an individual can stay in a particular location. If this duration is unusually long, or anomalies of patterns in an unfamiliar place, it may alert uncertainty or cognitive distress. Additionally, movement metrics like speed and acceleration also offer valuable insights. Erratic speed changes or repeated stopping may reflect agitation or desire to flee.

Another valuable metric is path entropy. This evaluates how random or how disordered an individual's movements are. Elevated path entropy often indicates aimless or directionless movement, which is a common sign of wandering. Low entropy implies more deliberate, goal oriented movement towards a familiar environment. Other useful indicators such as turning angles, how closely the current route matches the previous one and the likelihood of returning back to the familiar environment also helps to separate wandering behavior from normal standard mobility patterns.

We expand on traditional features by incorporating geo-contextual awareness through the use of geographic shape files. By mapping GPS movement data over maps detail infrastructure and environmental attributes. From this we derive context aware features such as terrain classification (urban, rural, near water), land type (residential, forest, commercial), and potential hazard zones (such as highways or rivers). This additional layer of inputs enriches the model to make more informed decisions by considering environmental risk alongside behavioral patterns of the patient. For example, wandering near a river at night would be treated as more critical than walking through a fenced neighborhood and would trigger a more urgent alert.

Time related variables including daily routine, weekday versus weekend behavior, seasonal fluctuations play a vital role in detecting wandering. This is especially important due to phenomena like sun downing, where the confusion in dementia patients often worsens in late afternoon or evening. By factoring these temporal cues, models can be fine tuned lowering the rate of false alerts and ensuring timely alerts are issued identifying genuine wandering events.

Through the integration of sophisticated feature engineering, flexible geo fencing boundaries, and strong temporal analysis, the system is designed to create a context aware adaptive platform. Its goal is to both identify and predict wandering behavior with high accuracy. Such foresight is the key to ensure safety and allowing early intervention in settings where continuous human monitoring is not available.

2.7 Sensors based Off-body Detection

In recent years, wearable health monitoring devices have drawn a lot of attention, particularly from dementia and older patients (Cote et al., 2021). One of the biggest challenges of these systems, particularly for those with dementia is its ability to maintain the device's constant touch with the body. Devices are frequently taken out, lost, or worn improperly due to cognitive loss, discomfort, and lack of awareness, which might result in missing or inaccurate data, for example, wearable device adherence is frequently low among dementia patients, with usage durations varying greatly and some cases of devices being worn for as little as six minutes. In order to verify data integrity and to raise an alert when the gadget is removed or not worn properly, off-body detection is very important. Research indicates that continuous wear is a behavioral issue as well as a technical one. For instance, highlighted that the success of long-term monitoring systems is directly impacted by older persons' frequently low adherence to wearable use in the absence of caregiver support or intelligent reminders (Fowe, Sanders, and Boot, 2023).

Specifically, research has demonstrated that wearable health monitors' efficacy in dementia care is contingent upon usability, comfort, and autonomy in addition to sensor performance (Yang et al., 2025). Patients or caregivers frequently refuse to use devices that are large, inconvenient, or necessitate constant contact. For this reason, in dementia care settings, wearable technology with built-in off-body sensing that requires little human input is highly preferred. Additionally, it has been suggested that these detection devices be integrated with remote monitoring platforms or caregiver alerts to guarantee prompt assistance and intervention (Sweeney et al., 2022).

In dementia care, it can be very challenging to keep wearable health monitoring equipment in continual contact with the body. To solve this issue, a number of researchers have suggested behavioural and design solutions. Using soft, textile-based wearables that are incorporated into clothes is one successful tactic that improves comfort and lowers the possibility of removal. For example, adding sensors to common clothing items like shirts or socks greatly increased adherence among senior users.

Furthermore, it has been demonstrated that automated off-body detection systems that employ capacitive or bioimpedance sensors increase dependability by disregarding or flagging data obtained when the device is not in contact with the skin. (Zheng et al., 2020) developed a wearable capacitive sensor capable of monitoring physiological signals such as breathing and pulse without requiring skin contact. The sensor's configuration including a porous dielectric layer and electrodes shaped as a disk at the bottom and a ring at the top elevated its ability to detect proximity variations. The specific design allowed the sensor to recognize non-contact scenarios through capacitance changes when an object was nearby.

Additionally, behavioral approaches such including caregiver alarms or reminder systems have been suggested. Also highlighted that when caregivers received warnings if a device was removed or reminders were included, individuals with dementia were more likely to continue proper device usage. Ergonomics advancements and the shrinking of wearable technology have also been beneficial. Participants were more obedient when the wearables were small, light, and had simple straps or fasteners, particularly if they looked like conventional accessories like pendants or wristwatches, according to a study by (Guu, Aarsland, and Ffytche, 2023).

Capacitive touch sensors are frequently used in wearable technology and consumer electronics to detect skin contact. When a conductive substance, such as human skin, is nearby, capacitive sensors identify variations in capacitance. Research indicates that capacitive sensors are appropriate for low-power, real-time wear monitoring in wearables due to its ability to reliably detect contact loss events (Geißler et al., 2024).

The Bioimpedance sensors measure physiological signals like heart rate and breathing. These sensors track electrical resistance variations between electrodes and skin that increase significantly when the device is taken off the body. Research indicates bioimpedance is sensitive to skin contact and hydration levels which enables it to detect off-body events effectively (Groenendaal, Lee, and Hoof, 2021).

Accelerometers and gyroscopes are combined in IMU sensors to detect orientation and motion. The health monitoring devices can be used to track posture, gait, and activity levels. IMUs assist in distinguishing human motion patterns from static or erratic movements that happen when a gadget is placed down on a table or left unattended (Kim et al., 2021). IMUs are less reliable when it is used by themselves to detect direct skin contact, but when combined with other sensor data, they provide useful context.

The three types of sensors can be combined to improve the off-body detection's accuracy and dependability. In various researches Sensor fusion techniques have been suggested to enhance classification performance and lower false positives, especially in applications that are vital to health, like in the case of dementia care.

Despite significant progress in wearable health monitoring devices, numerous critical deficiencies persist, especially in dementia treatment. The literature indicates that a principal problem is maintaining persistent device-to-skin contact, frequently undermined by cognitive impairment, pain, and insufficient user awareness. Although capacitive, bioimpedance, and IMU sensors exhibit potential for off-body detection, each possesses inherent limitations when utilized in isolation. Additionally, current solutions frequently appear to be not optimized for the comfort and efficacy of dementia patients or do not integrate with caregiver alert systems. Despite the fact that the majority of commercial wearables are based on wristbands with off-body detection, these are often ineffective for dementia patients who may remove them due to discomfort, forgetfulness, or agitation, thereby limiting their practical impact on caregivers. The objective of this study is to address these gaps by investigating off-body detection in multiple wear locations beyond the wrist, improving detection accuracy through sensor fusion, and ensuring real-time communication with caregivers to facilitate timely intervention and support.

3 The Implementation

3.1 High Level Architecture

The system comprises two key components: IoT devices and a web platform. Our system consists of two categories of IoT devices: LoRa end devices and LoRa gateway devices. LoRa end devices function as wearable device within the network, transmitting patients' GPS locations obtained from the GPS NEO-6M module via the LoRa medium. In the prototype, the wearable device only uses GPS data to send its location as the tracking mechanism. However, these end devices can be extended with additional sensor modules to collect various data from patients, including health metrics like heart rate and movement, among others. LoRa wearable devices can be positioned on the patient's hand or can be adapted to be attached to various other parts of the body, such as the belt, arm, or clothing. The LoRa-enabled home device situated in the home of the dementia patient, linked to the web platform through the internet connection. Sensory information transmitted from the LoRa device is collected through home devices and relayed to the web application via the HTTP protocol for real-time monitoring and geo-fencing features.

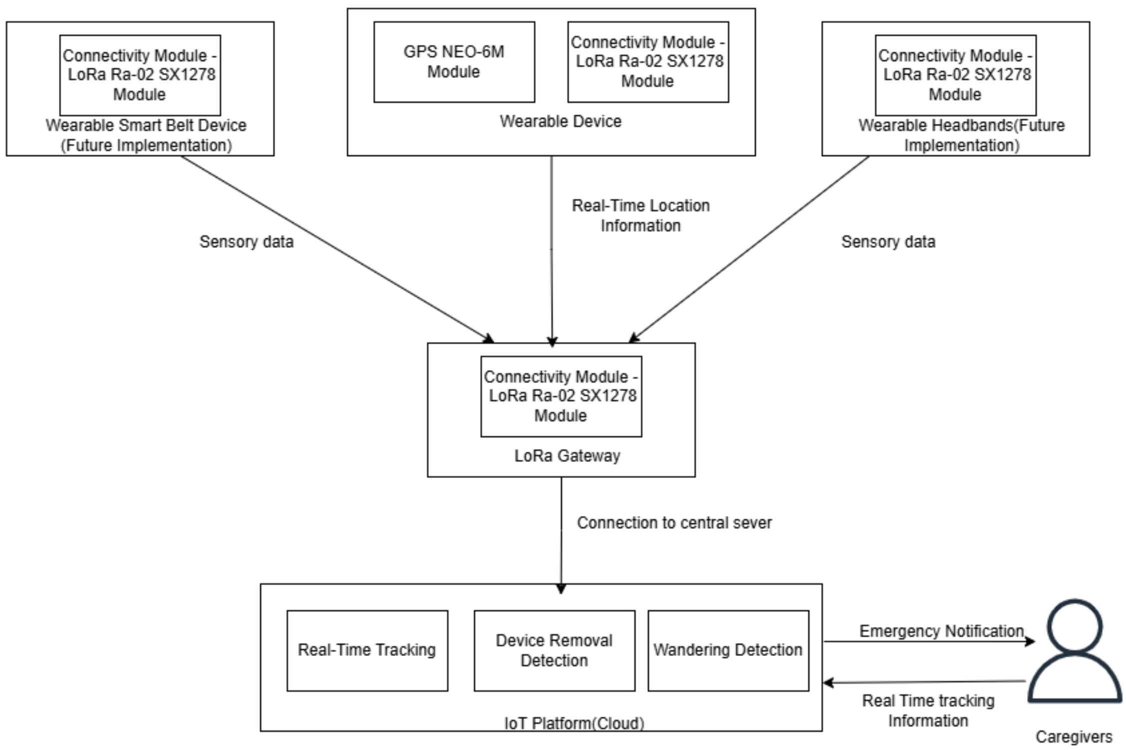

Figure 9: High level architecture

3.2 LoRa module

The devices are equipped with a LoRa module that enables the transmission and reception of data packets via the LoRa medium. For the prototype LoRa Ra-02 SX1278 module used and it connected with NodeMCU ESP32 WiFi Bluetooth Dual Mode IoT Dev Board. The antenna utilized for the LoRa module is a 433MHz RF antenna with a gain of 2-3 dBi. The price of the LoRa module along with the antenna is Rs. 1750.00. Below are the settings that have been configured for the LoRa module in the prototype IoT devices.

```
// Change sync word (0xF3) to match the receiver
// The sync word assures you don't get LoRa messages from other LoRa transceivers ranges from 0-0xFF
  LoRa.setSyncWord(0xF3);
  LoRa.setTxPower(10);
  LoRa.setSpreadingFactor(10);
  LoRa.setSignalBandwidth(62.5E3);
```

Listing 1: LoRa ESP32 configurations

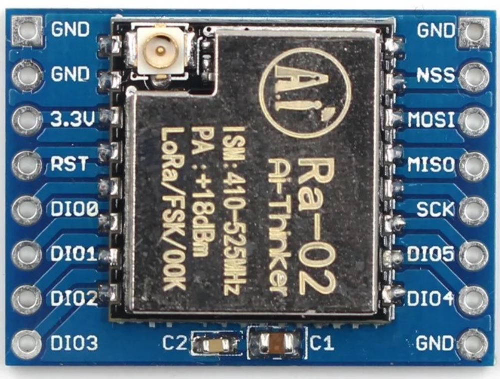

Figure 10: LoRa Ra-02 SX1278 Module(*MD0532 - Tronic.lk* 2025)

Figure 11: RF 433MHz Antenna 2-3 dBi(*MD0164 - Tronic.lk* 2025)

3.3 Wearable Device(End Device)

The wearable device is developed to reduce its dimensions while enhancing user-friendliness for patients. The LoRa module is smaller and lighter than other cellular modules. In the prototype, we use the ESP32 module instead of an Arduino board to reduce the size. The ESP32 module has been included for development purposes, but will be removed in the actual deployment of IoT devices in a real-world environment. This change means that the contributions of LoRa, GPS, and other sensors will affect the overall size. For the GPS module Ublox NEO-6M GPS Module Aircraft Flight Controller for Arduino module used and it costs around Rs. 1550.00. Wearable devices send two types of the data packets which are STS(Status) data packets, GPS(GPS) data packets. The STS data packet is used to send the connection request through the LoRa network, and the ACK data packet is used to send a successful connection message to the wearable. GPS data packet used for send GPS locatin data to the web application.

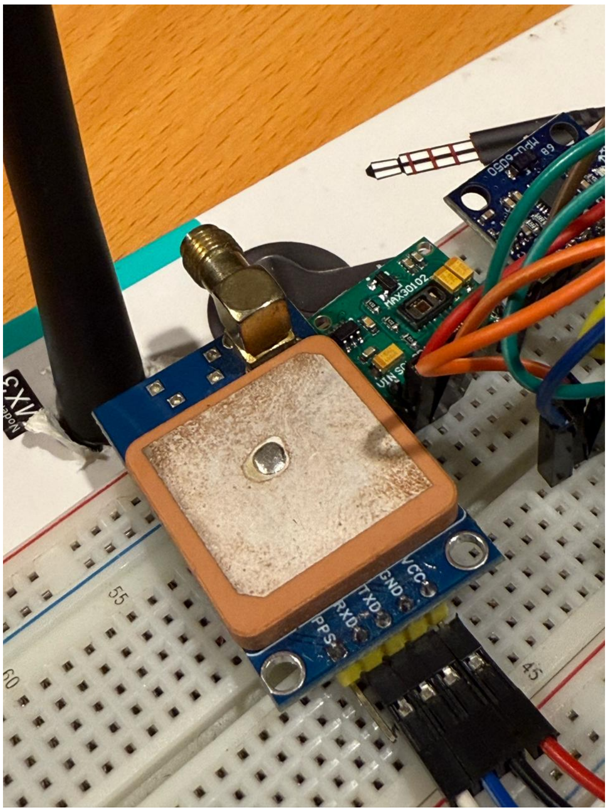

Figure 12: Ublox NEO-6M GPS Module(*MD0153 - Tronic.lk* 2025)

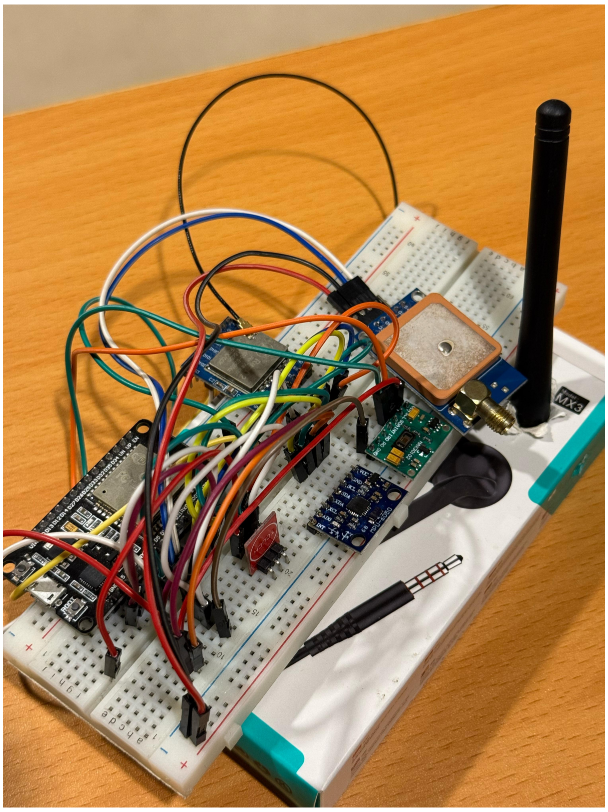

Figure 13: Wearbale device

GPSce:3c:da:77:38:e2N6.901766E79.861526TM1745315259

Figure 14: Example GPS data send by wearable device

Entry in data packet	**value**
Data type	GPS
Source mac address	e:3c:da:77:38:e2
Latitude	N6.901766
Longitude	E79.861526
Generated timestamp	1745315259

Table 2: Decoded GPS data packet

3.4 Home Device(Gateway Device)

The home device is a LoRa gateway that captures data packets from a wearable device and sends them to a web application. The home device contains a LoRa RA-02 SX1278 module, along with a NodeMCU ESP32. The ESP32 is used to connect to the internet via Wi-Fi. Home devices are static LoRa nodes that do not move, and the antenna needs to be placed outside of the house to provide maximum coverage. Each patient will have both a wearable device and home devices; therefore, at any given time, the number of gateway devices is equal to the number of wearable devices in the system. The home device will capture data packets from nearby wearable devices, with a balanced frequency limit set by a protocol to optimize and reduce internet bandwidth usage.

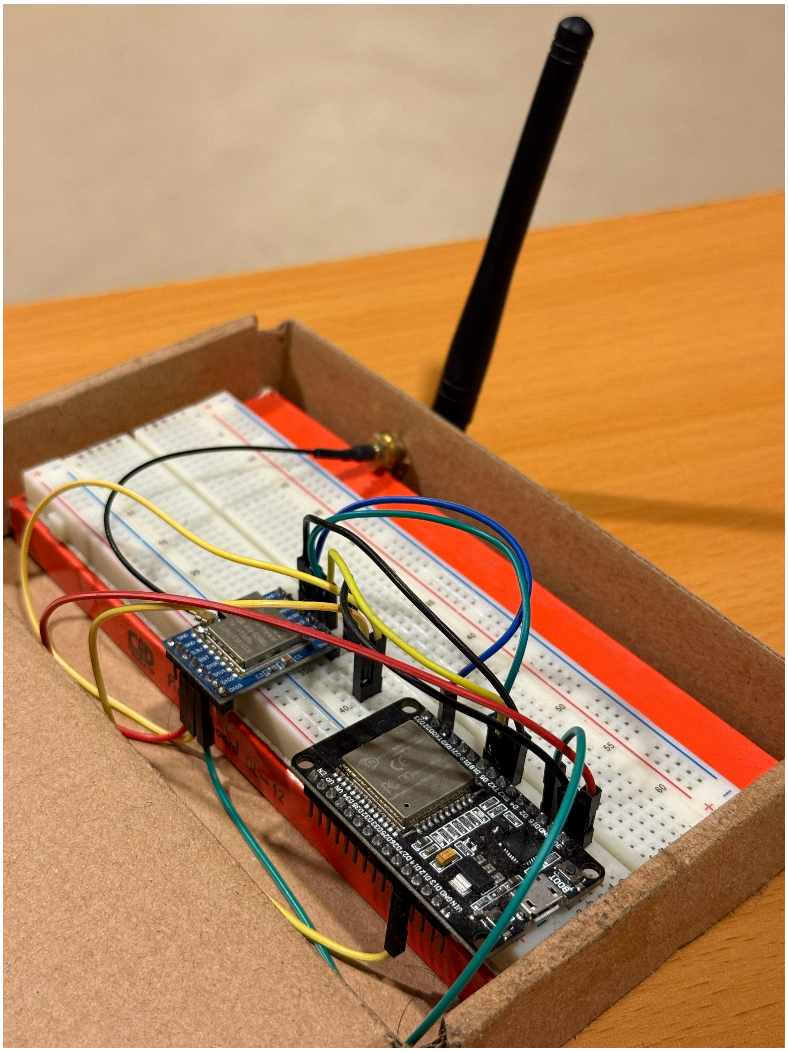

Figure 15: Home device

3.5 Dynamic Geo-fencing Using ML

In this research, we designed a dynamic geofencing-based system to detect and predict wandering behavior among dementia patients using real-time GPS data and machine learning models. The system architecture comprises multiple stages including data preprocessing, zone labeling using shapefiles, feature extraction, zone classification, and wandering prediction using time-series models.

3.5.1 Haversine Distance for Movement Filtering

Raw GPS data collected from wearable or IoT devices often includes jitter or redundant records, especially when the subject is stationary or moving slowly. To ensure that only meaningful movement is captured, we apply the Haversine formula to calculate the real-world distance (in meters) between two consecutive latitude and longitude points.

This method is particularly useful for dementia cases, as subtle movements like pacing indoors can falsely appear as transitions. By applying a minimum threshold (e.g., 5–10 meters), we filter out non-significant noise and preserve meaningful mobility data.

```
from geopy.distance import geodesic

def haversine(lat1, lon1, lat2, lon2):
    return geodesic((lat1, lon1), (lat2, lon2)).meters
```

Listing 2: Haversine Function

This improves both data quality and model performance, ensuring that wandering behaviors—which often involve broader, spatially erratic movements—are accurately detected.

3.5.2 Shapefile-Driven Geospatial Intelligence

To perform geofencing, we use locally stored OSM-derived shapefiles rather than relying on online APIs. This decision was driven by three key factors:

- **Edge Processing:** Devices used for tracking dementia patients often have limited computational resources. Downloading and storing only the relevant `.shp` tiles based on the patient's starting location helps minimize memory usage and supports efficient local processing.

- **Privacy:** Monitoring dementia patients involves highly sensitive personal data. By avoiding real-time API calls and instead relying on locally stored shapefiles, the system ensures greater control over data privacy and reduces exposure to third-party services.

- **Offline Functionality:** In many rural or indoor environments where internet connectivity may be unreliable or unavailable, having preloaded shapefiles ensures the system continues to function without interruptions.

To minimize storage while maximizing spatial awareness, we initially extract only OSM tiles covering a buffer zone (e.g., 3–5 km) around the patient's home or care center.

These files contain layers like buildings, roads, land use, natural features, and points of interest.

3.5.3 Using OSM Attributes for Dementia-Specific Zone Classification

Each polygon or line feature in the shapefiles includes a key attribute fclass which represents the semantic type of the feature

We tailored a dementia-sensitive classification system by grouping fclass values into three categories:

Zone Type	**OSM `fclass` Examples**	**Dementia Rationale**
Safe	residential, path, park	Familiar and non-threatening environments such as home neighborhoods, walking paths, or parks that are often part of the patient's daily routine.
Warning	secondary, industrial, commercial	Areas that may confuse dementia patients due to unfamiliar layouts, noise, or increased social interaction. These zones increase the likelihood of disorientation.
Danger	river, forest, railway, motorway	High-risk environments where accidental injury, getting lost, or restricted access may occur. These zones should trigger immediate alerts.

Table 3: Zone classification based on OSM `fclass` for dementia-oriented geofencing

```python
# Example mapping
def classify_zone(fclass):
    if fclass in ['residential', 'park', 'path']:
        return 'Safe'
    elif fclass in ['industrial', 'commercial']:
        return 'Warning'
    elif fclass in ['river', 'forest', 'railway']:
        return 'Danger'
    return 'Default'
```

Listing 3: Zone Classification

By dynamically assigning these labels to GPS coordinates using spatial joins (gpd.sjoin), we provide real-time context to patient movements.

3.5.4 Polygon Creation and Dynamic Geofencing

The spatial zones from shapefiles are converted into geofencing polygons using tools like Shapely. Each polygon acts as a zone boundary. When a GPS point enters a polygon, its type (Safe/Warning/Danger) is assigned *geofabrik.de* n.d.

```
from shapely.geometry import Point

point = Point(longitude, latitude)
for polygon in danger_zones:
    if point.within(polygon):
        return 'Danger'
```

Listing 4: Dynamic Labeling for Points

In contrast to static geofences (e.g., circular areas), our polygonal geofences adapt to the actual environment (e.g., river path), making them especially effective for dementia patients, who may stray unpredictably.

3.5.5 Feature Engineering for Wandering Detection

From the spatiotemporal GPS data and zone classifications, we extracted the following features

- **Time in Zone:** Measures the dwell time spent in each labeled zone (Safe, Warning, Danger) to assess prolonged presence in risk-prone areas.
- **Speed and Acceleration:** Computed between each GPS timestamp to detect abnormal movements such as sudden bursts or halts.
- **Zone Transition Count:** Captures the number of times a patient switches between different zones, which may indicate restlessness or aimless wandering.
- **Path Entropy:** Quantifies the randomness of the walking path. Higher entropy is associated with disoriented or aimless movement patterns.
- **Direction Deviation:** Measures sudden changes in walking direction, which may signify confusion or erratic behavior.

- **Time of Day:** Includes temporal context since wandering behavior is more prevalent during late hours due to sundowning effects in dementia.

These features were normalized and structured into sliding time windows (e.g., 10-minute sequences) to capture temporal movement dynamics for further analysis and model training.

3.5.6 LSTM-Based Personalized Machine Learning for Wandering Prediction

To address the task of predicting wandering behavior in dementia patients, we developed a Long Short-Term Memory (LSTM) based model that processes real-time movement data to predict the patient's next location. LSTM networks are particularly well-suited for this task because they can capture long-term temporal dependencies, remember sequential patterns over time, and handle irregular time gaps in the input data — properties that are crucial when modeling real-world GPS trajectories where movement is not uniform. Traditional machine learning models like Random Forests, Support Vector Machines (SVM), and even basic feedforward neural networks were considered. However, these models generally assume independent samples and lack the capability to model temporal sequences effectively. In contrast, LSTM networks are explicitly designed to learn from ordered data, making them more appropriate for forecasting future positions based on historical movement patterns. Therefore, we prioritized LSTM over conventional models to better capture the evolving wandering behaviors of dementia patients and enable real-time, adaptive prediction of location Khaertdinov, Semerci, and Asteriadis, 2021.

The LSTM model was constructed with the following architecture:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, Bidirectional
    , LayerNormalization

model = Sequential([
    Bidirectional(LSTM(64, return_sequences=True), input_shape=(
    sequence_length, len(features))),
    LayerNormalization(),
    Dropout(0.3),

```

```
    Bidirectional(LSTM(64, return_sequences=False)),
    LayerNormalization(),
    Dropout(0.3),

    Dense(32, activation='relu'),
    Dense(2)  # Latitude, Longitude
])

model.compile(optimizer="adam", loss="mse")
model.summary()
```

Listing 5: LSTM model construction

The model architecture consists of several layers. Initially, a Bidirectional LSTM layer with 64 units processes the sequential data, capturing both past and future context. Bidirectional LSTMs are important for understanding movement patterns where the future behavior may depend on both previous and subsequent data points. The output from the first LSTM layer is passed to a LayerNormalization layer to stabilize activations and a Dropout layer to prevent overfitting by randomly dropping neurons during training. A second Bidirectional LSTM layer, also with 64 units, processes the sequence and outputs the final prediction. This layer does not return sequences, as the task is to predict a single output for each sequence. After the LSTM layers, the model includes a Dense layer with 32 units and ReLU activation to learn more complex relationships between the hidden states, followed by a final Dense layer with 2 units to predict the next latitude and longitude.

The model is compiled with the Adam optimizer, which adapts the learning rate based on the model's performance during training, and Mean Squared Error (MSE) as the loss function, as the task involves predicting continuous values. The model is designed to be trained on real-time data, using past sequences of the patient's movements to predict future coordinates. By learning typical movement patterns, the model can detect deviations, which may indicate wandering behavior.

The use of Bidirectional LSTM layers enables the model to incorporate both past and future context when making predictions, which is crucial for detecting wandering patterns where the patient may move in unexpected ways. LayerNormalization improves the efficiency of training by stabilizing activations, while Dropout prevents the model from overfitting to the training data, ensuring it generalizes well to new, unseen movement data. The ReLU activation function introduces non-linearity into the model, which is necessary for capturing complex relationships in the data. Finally, the choice of the Adam optimizer accelerates the training process by adapting the learning rate based on the model's performance, ensuring efficient convergence.

This model is specifically designed to handle real-time data, continuously updating as new movement information becomes available, and provides real-time predictions of a patient's future location, helping to detect wandering behavior promptly and effectively.

3.6 Web Application

For the prototype web application created with Node.js and the Express framework to handle data packets transmitted from a LoRa home device. The web application interfaces with a PostgreSQL database that manages authentication and tracks patients using the MAC addresses of their wearables. Following is the ER diagram of the database (Figure 16). The database schema consists of three main tables: device, location, and profile. The 'device' table stores information about all registered devices in the systems, including a unique MAC address, a human-readable name, the last known GPS location (as a geography point), the device type (such as an end device or a gateway), the current status, and the last time the device was active. The location table records location events of devices, including a unique location ID (generated using UUID), the MAC address of the source device being tracked, the location point, the MAC address of the detecting gateway device, and the time of the record. Both MAC addresses in this table reference the device table and are set to NULL if the associated device is deleted. The profile table holds user information such as username, display name, password, telephone number, and links each user to both an end device and a gateway device via foreign keys to the device table.

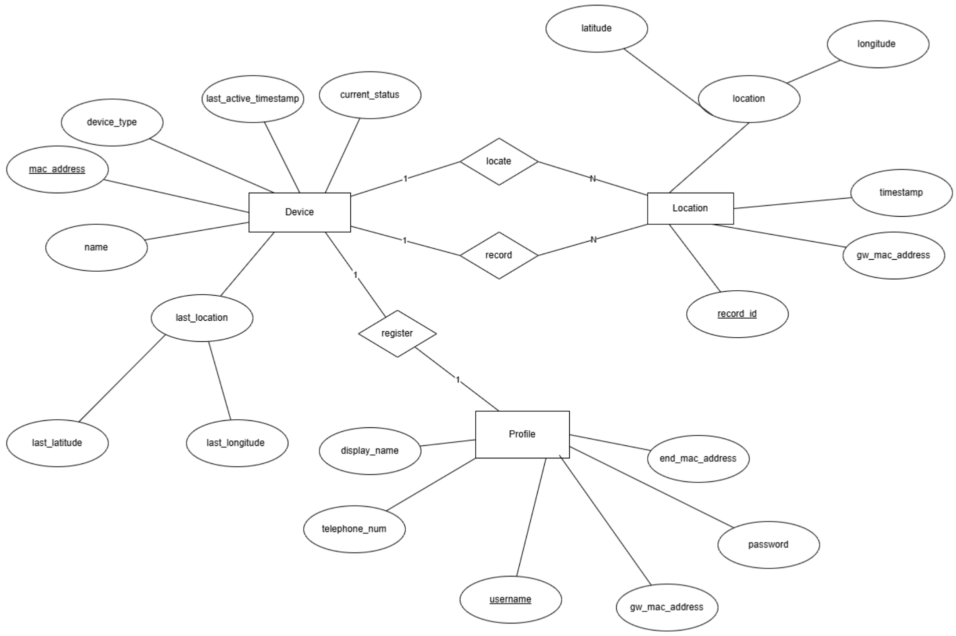

Figure 16: ER Diagram

The prototype web application contains a login page and the dashboard page which includes a map interface developed for monitoring the real-time location of dementia patients. Every dementia patient using the system is equipped with wearable devices and home devices, each uniquely registered with its MAC address. Once the login is successful, the dashboard of the web application displays the details of the devices based on their current status and location (Figure 17). Caregivers of dementia patients can log into the web application at any time with their credentials to access the patient's information (Figure 18).

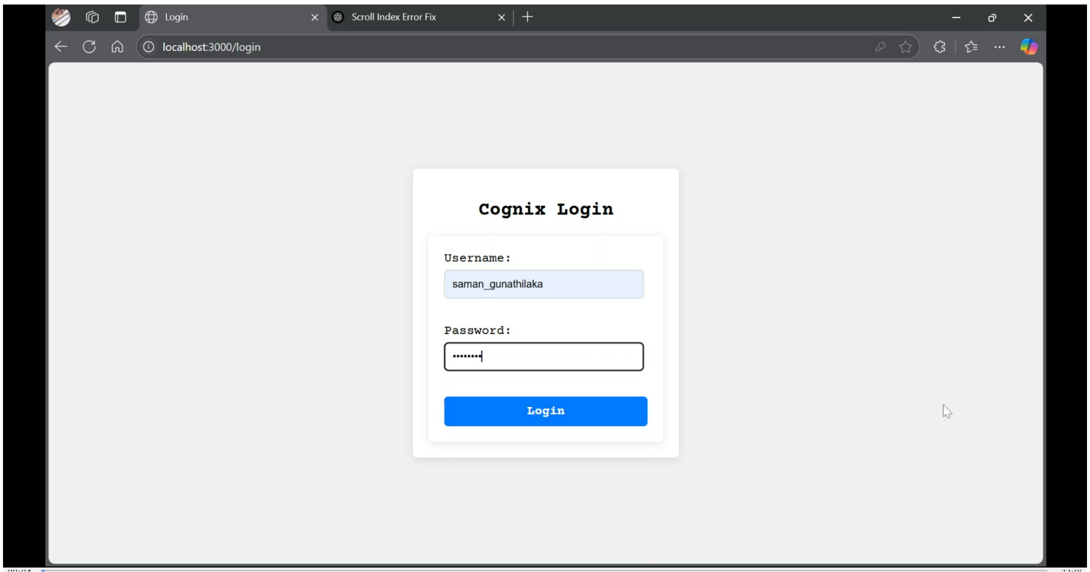

Figure 17: Login Page of the Application

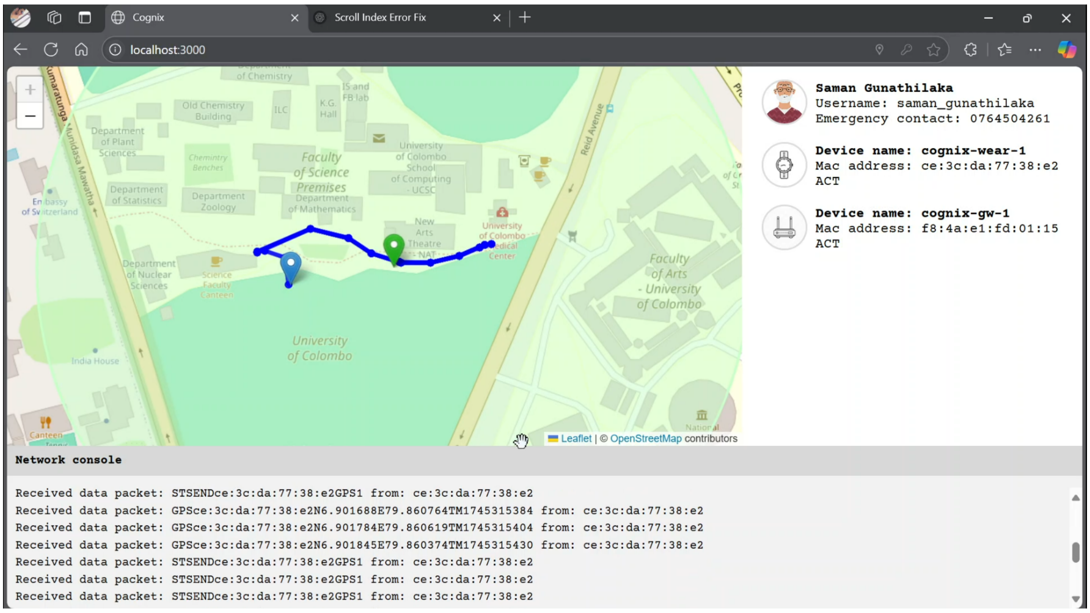

Figure 18: Dashboard of the Application

3.7 Protocol for Multiple Home Devices

The system uses multiple home devices to ensure extensive coverage for wearable devices, with industrial-grade home devices capable of covering distances between 600 meters to 1 kilometer within the patient's neighborhood. Every home device is used to collect positional data from wearable devices. When a wearable device connects or moves out of the range of one home device, the system automatically identifies and connects to another suitable home device within the network. This works similar to the handoff in cellular networks where mobile devices change their towers (Seshan, Balakrishnan, and Katz, 1997). Wearable devices periodically send out status (STS) messages to communicate their connectivity over the LoRa medium. When a home device receives an STS message from a wearable device, it registers the wearable device with the home device if the home device is available to capture GPS data from it. The home device can collect data packets from various wearable devices and may frequently collect GPS location information. This will increase the internet bandwidth consumed by the home devices and needs to be balanced between other home devices. To improve the connectivity and internet bandwidth usage, we introduce a routing protocol to provide a static route in a broadcast LoRa network.

When a wearable device comes online, it sends STS messages to nearby home devices. All the home devices within the range of wearable will receive this message since LoRa operates in a broadcast manner (Figure 19).

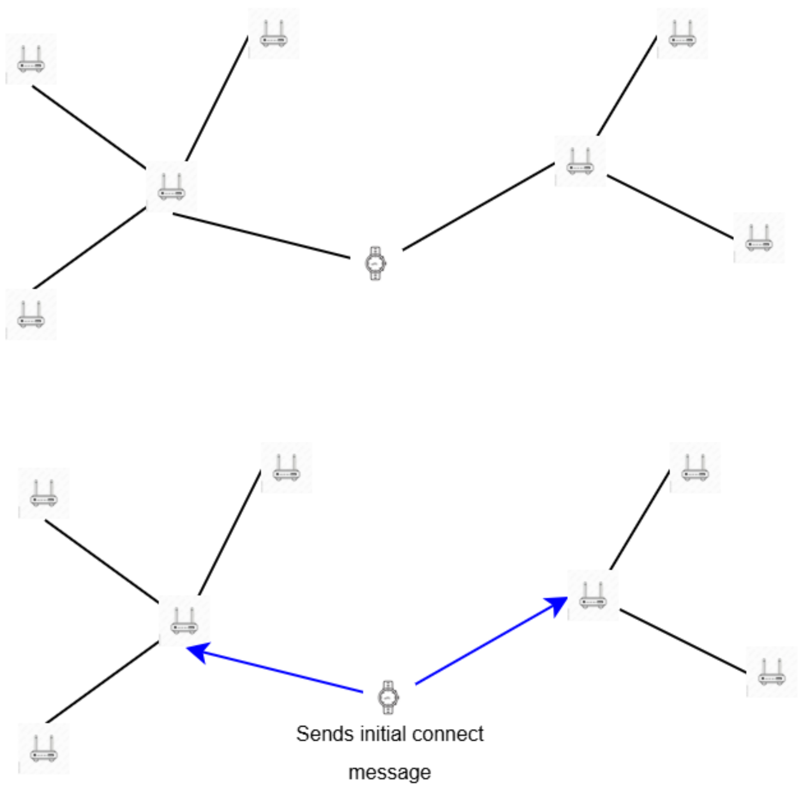

Figure 19: Initial connection process of wearable device

The STS data packet contains the source MAC address and a list of MAC addresses of intermediate home devices, which are added as a stack data structure. This stack data structure is used to send an ACK message back to the wearable after registration with the web application. When an STS data packet is broadcasted by an intermediate node, the MAC addresses of the intermediate home device will be added to the stack, and the TTL (Time to Live) value will be reduced by one.

STS66:31:1d:07:16:b4,58:b7:9f:e2:00:91,4f:1a:6f:ca:de:e1TTL3GPS1

Figure 20: Example STS message broadcasted by two home devices

ACK66:31:1d:07:16:b4,58:b7:9f:e2:00:91,4f:1a:6f:ca:de:e1TTL3GPS1

Figure 21: Example ACK message broadcasted by registered home device

If the home device is occupied or locked with multiple wearable devices, it sends out an STS message to nearby home devices.Once the STS message is received by the available home device, it sends an HTTP request to the web application to lock the wearable device to that home device. After the wearable device is locked, other home devices will not process the STS/GPS data from that wearable device, as it is confined to a specific route in the LoRa network (Figure 27).

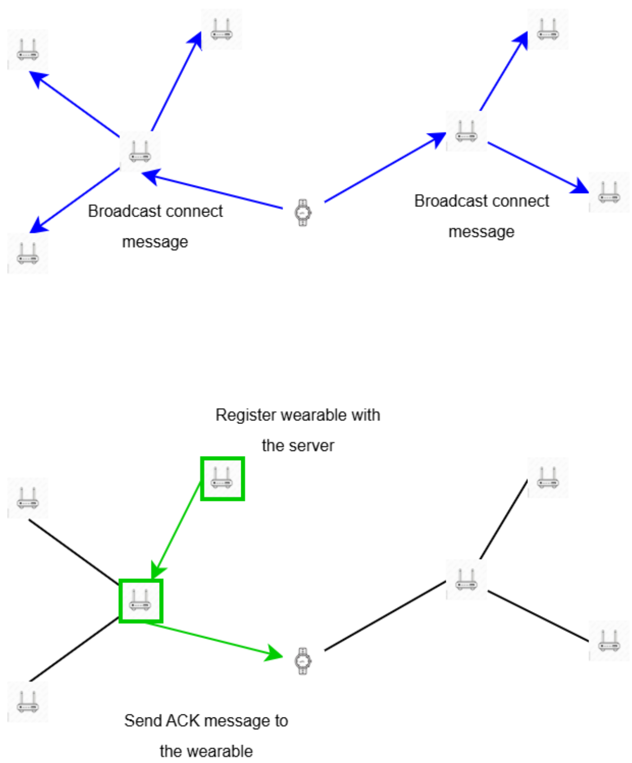

Figure 22: Broadcasting STS message to connect available home device

Once a home device is locked with a wearable device, an acknowledgment (ACK) message will be sent to both the wearable device and the intermediate home devices along the communication path. This message updates their broadcast table and capture table. Each home device in the network maintains two tables: a capture table and a broadcast table. Capture a table to maintain a list of MAC addresses of wearable devices to capture data packets from given home device and send them to the web application. At a given time, only one home device will be registered with a specific wearable device, which eliminates duplicates of the same data packet sent to the web application by multiple home devices. The broadcast table is similar to the capture table, where the MAC address of the wearable device and a specific TTL value are stored. Home devices will only broadcast the message if the data packets match the source MAC address and the TTL value provided in the broadcast table. Using this algorithm, we can minimize the frequent broadcasting that happens in the LoRa network and provide network-wide load balance (Figure 23).

MAC Address	**TTL value**
12:34:56:78:9A:BC	3
FE:DC:BA:98:76:54	2
01:23:45:67:89:AB	4

Table 4: Example capture table

MAC Address	**TTL value**
00:1A:2B:3C:4D:5E	3
11:22:33:44:55:66	1
AA:BB:CC:DD:EE:FF	5

Table 5: Example broadcast table

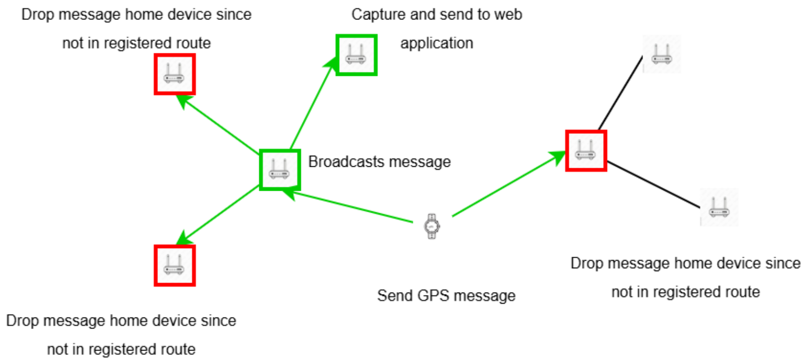

Figure 23: Routing the GPS messages

```
function handleMessage(message):
    if (message.type == "STS" and message.hop_counter > 0){
        if homedevice.status == BUSY{
            decrement hop counter by 1
            message.mac_stack.add(homedevice.mac)
            broadcast message
        }else{
            bool reg = register(message.source_mac, homedevice.mac)

            if reg == True{
                send ACK message
                capture_table.add(messagemac_stack.top(), message.
   hop_counter):
            }else{
                drop message
            }
        }
    }else if (message.type == "ACK" and message.mac_stack.top() ==
   homedevice.mac){
        broadcast_table.add(message.mac_stack.top(), message.
   hop_counter):
        message.mac_stack.pop()
        increment hop counter by 1
        broadcast message
    }else if( message.hop_counter > 0){
        if capture_table.contains(message.source_mac, message.
   hop_counter){
            send message to web application
```

```
        }else if (broadcast_table.contains(message.source_mac, message.
    hop_counter)){
            decrement hop counter by 1
            broadcast message
        }else{
            drop message
        }
    } else {
        drop message
    }
}
```

Listing 6: Home device algorithm

3.8 Multisensor-Based Off-Body Detection

This research adopts a multisensor based detection mechanism to precisely detect the wearing or removing of the wearable. The system combines three different types of sensors: capacitive touch sensor (TTP223), a photoplethysmography (PPG) sensor (MAX30101), and an inertial measurement unit (IMU) sensor (MPU6050). The different data streams from each sensor when combined allow reliable context aware inference of the device's condition. This is due to fusion ofsensors that improves the weaknesses of single sensors, making the overall results accurate and frequent in a wide range of situations.

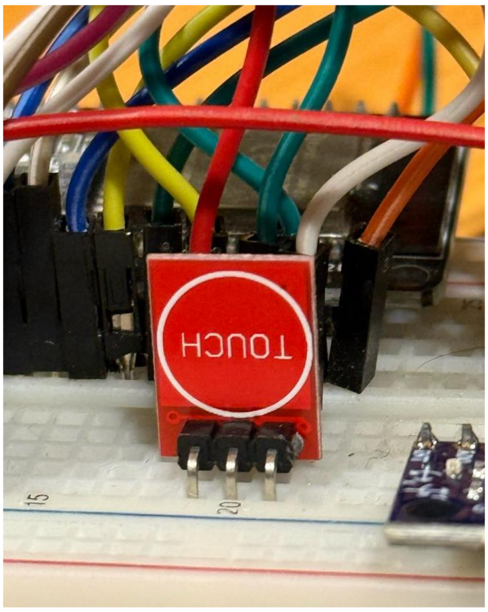

Figure 24: TTP223 capacitive touch sensor

Changes in capacitance that indicate contact or closeness are used by the TTP224 capacitive touch sensor to detect the presence of a human body. It acts as the initial line of detection when determining if gadget is in direct contact with the skin. Since it reacts rapidly and uses less processing power this sensor can be appropriate for real-time monitoring. However by itself it can be prone to inaccurate results as it may sense touch when placed near conductive materials such as metal surfaces or when exposed to high humidity. Furthermore it's accuracy is limited when used alone due to it's inability to distinguish between human skin and other conductive materials.

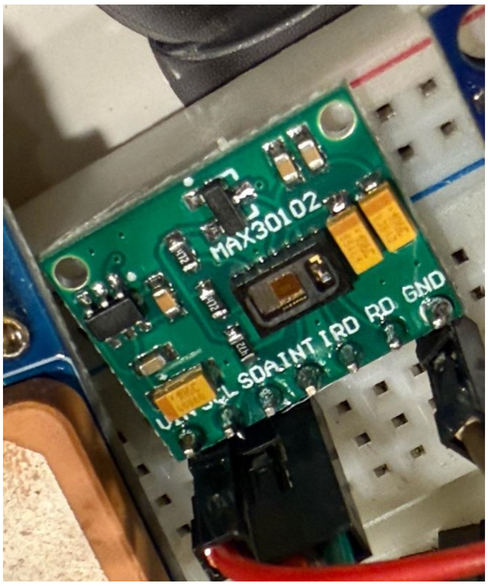

Figure 25: MAX30102 bioimpedance sensor

The MAX30101 bioimpedance sensor, uses photoplethysmograpghy to measure psychological signals and is frequently used for heart rate and SpO2 monitoring. It shines light onto the skin and measures the change in reflected light brought by variations in blood volume. When it comes in contact with the human skin the device records a steady pulse waveform. Due to this it is quite good at confirming true human contact differentiating between actual skin and artifical conductive surfaces. Although it's accuracy the MAX30101 has drawbacks. It is very sensitive to motion artifacts, ambient light interference and skin elements like dryness or hair, which may distort or inhibit readings. It also needs stable and secure skin contact to produce clear signals.

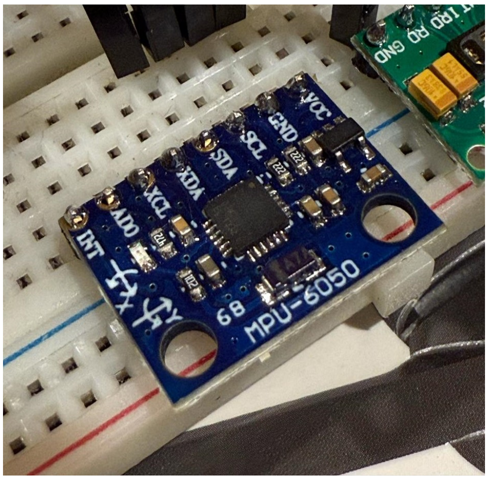

Figure 26: MPU6050 sensor

The MPU6050 sensor consists of a three-axis gyroscope along with a three-axis accelerometer, which enables the sensor to output data regarding motion, orientation, and acceleration. The sensor was crucial in determining whether the device is stationary or in motion, thereby enabling the detection if a user is active, resting, or if the device has been removed and kept somewhere else. For example, motionless posture combined with lack of contact gives a hint of removal, while similar quiescence when touch and heartbeat are continuously active suggests that the user is merely resting. The IMU sensor cannot confirm by itself the existence of contact with the skin and may incorrectly interpret an idle device placed in a bag or on a tabletop as being worn.

The system detects Off body events with greater accuracy by integrating the outputs of all three sensors. The specific faults of each sensor are minimized by the sensor fusion technique which also allows to comprehend the context and surroundings of the device more thoroughly. The system can be certain if for example the motion sensor reports no activity, the heart rate sensor does not detect a pulse and the capacitive touch sensor indicates loss of contact. On the other hand the gadget is verified to be worn and in use if the PPG and touch sensors both display accurate data and the IMU pickups up activity.

Rule based logic is used to achieve this multisenor technique which can subsequently be extended to include machine learning for more dynamic and adaptive detection. If none of the sensors detect any movement, contact, or phsychological data, the device might be categorized as removed according to a standard logical framework. In spite of motion the device is considered worn if touch and phsychological data are present. The terms "uncertain" or "needs verification" are used to describe circumstances where only one or two sensors produce contradicting data. This can be lead to a result in a prompt for user confirmation or additional monitoring.

Take the rule-based logical framework as an example. Physical touch is monitored by the TTP223 device. However the technology cross-verifies using motion and biometric data, because it is unable to differentiate between skin and other materials. Body movement is tracked by the MPU6050. Removal is suspected when the motion data shows the gadget has switched from active movement to immobility and the touch sensor detects lack of contact or unchanging input. Lastly, the MAX30102 detects the pulse of a human. Within a predetermined window, the system verifies that the device is no longer worn if no valid heartbeat is detected.

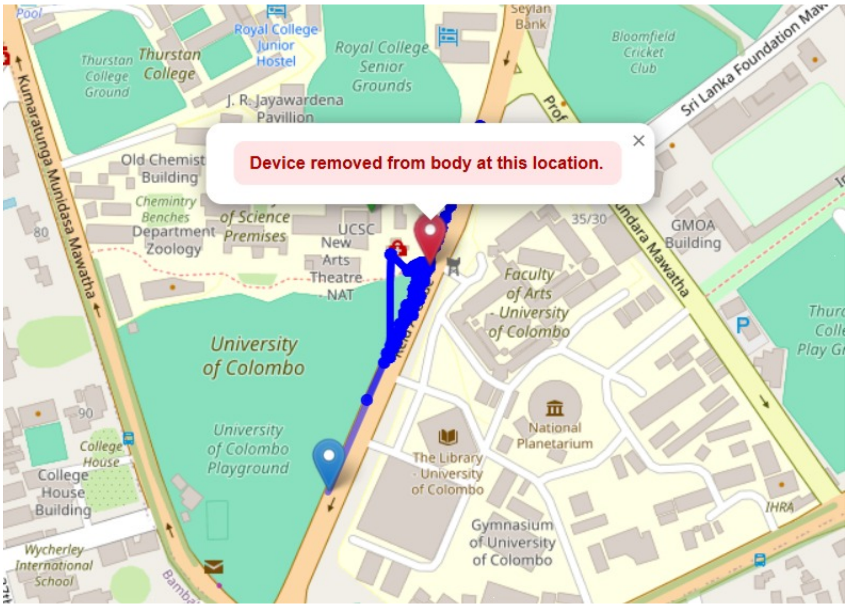

Figure 27: Off-Body Detect alert web notification

The three sensors work together to provide a number of significant benefits. By increasing redundancy it ensure that the system keep functioning even in the event that one sensor fails. Additionally it improves context awareness which enables the device to distinguish between subtle situations like a user napping, the device being worn loosely or it being carried in a bag. Furthermore the multisensor approach improves the reliability of alarms provided to the caregivers or monitoring systems and dramatically lowers possibility of false positives.

The ESP32 microcontroller processes all sensor data in real time which reads the inputs, executes the detection logic and sends outcome via LoRa to a remote monitoring system. An instant alert is sent out if the sensor fusion logic determines that the device has been taken out of the user's body. Through the embedded GSM/Internet module that is linked to the central server the caregivers will be automatically notified by SMS. If the person may be in danger the caregivers can act quickly because of this SMS which acts as an urgent real time alert. At the same time the event is recorded and shown on webs based monitoring platform for the project which provides the exact GPS coordinates of the site where the removal of the device took place. In order to give caretakers or medical personnel a visual reference to react promptly, the system marks the location on live map interface using the last known position from the LoRa transmitted GPS data. Both real time response and historical tracking of removal events for additional behavioral analysis or emergency intervention are guaranteed by this alert system which consists of SMS and web notifications.

Touch (TTP223)	**Pulse (MAX30101)**	**Motion (MPU6050)**	**Inference**	**Test Scenario Description**
Detected	Pulse present	Active	Device is securely worn and in use	User is walking, moving hand, or performing daily activities while wearing the device properly.
Detected	Pulse present	Idle	Device is worn, user is at rest	User is sitting or sleeping while the device is snug on the wrist or arm, generating pulse and touch data with no movement.
Not Detected	No pulse	Idle	Device is removed	Device is placed on a table or shelf where it is motionless and not in contact with the skin.
Not Detected	No pulse	Active	Device removed but moving (e.g., bag)	Device is carried in a bag or vehicle—detecting movement but no skin contact or pulse.
Detected	No pulse	Idle	Device may be loosely worn or obstructed	Device is loosely worn or shifted (e.g., worn over clothing or tilted), causing improper skin contact and loss of pulse signal while still registering touch.
Not Detected	Pulse only	Idle	Inconsistent state – verify contact	The sensor is manually triggered under a controlled condition (e.g., fingertip lightly pressed to PPG sensor without full skin contact over touch pad) to simulate a borderline/uncertain state. Useful for anomaly detection testing.

Table 6: Off-Body Detection Scenarios Based on Sensor Fusion

In conclusion, a strong and contextually aware off body detection method is produced by combining the TTP223 capacitive touch sensor, MAX30101 bioimpedance sensor and MPU6050 IMU sensor. By combining phsychological,physical, and motion based data the system correctly detects whether the device is securely worn or has been withdrawn. The constraints of each sensor are minimized by this multisenor fusion technique which enables precise detection in a range of real world situations such as movement, rest, loose,contact, or intentional removal. When the system detects a device removal event it instantly notifies the authorised caregiver via SMS and updates the web based monitoring dashboard with the device's last known GPS location and visual notification. This dual alert method promotes safety and situational awareness enabling cargivers to respond quickly and effectively to any wandering episodes or crises. This implementation is a crucial component of assistive wearable technology for dementia care and vulnerable user monitoring because it combines dependable sensor input, clever fusion logic and real time warning systems.

4 The Results and Analysis

4.1 LoRa Wearable with Single Home Device

The experimental setup consists of a home device prototype and a wearable device prototype, both deployed in the UCSC ground area for conducting the experiment. Here are the tracking details displayed on the dashboard of the web application.

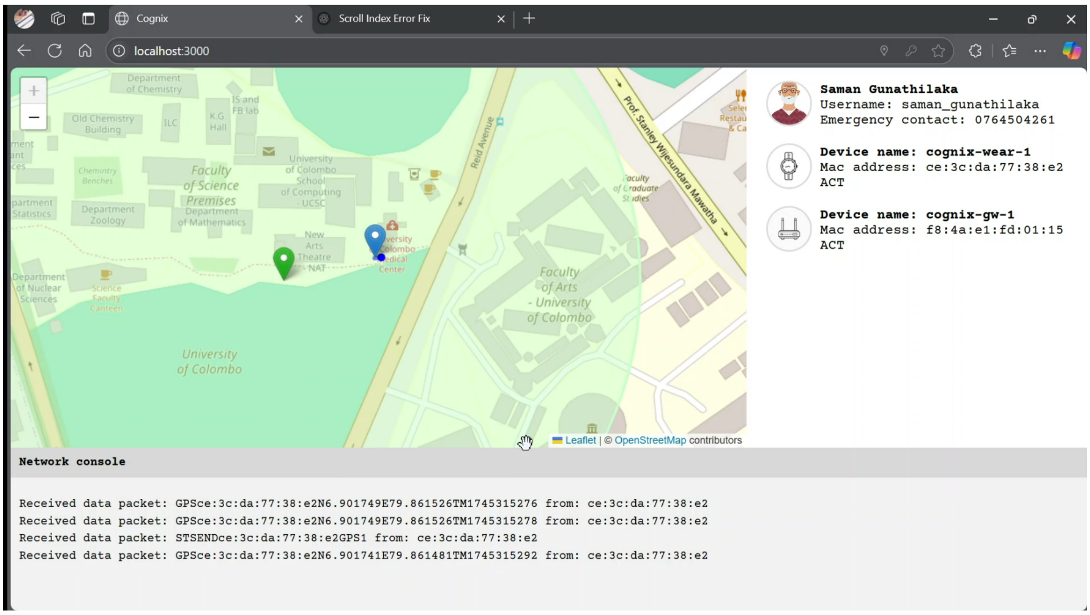

Figure 28: Experiment - Web application interface - 1

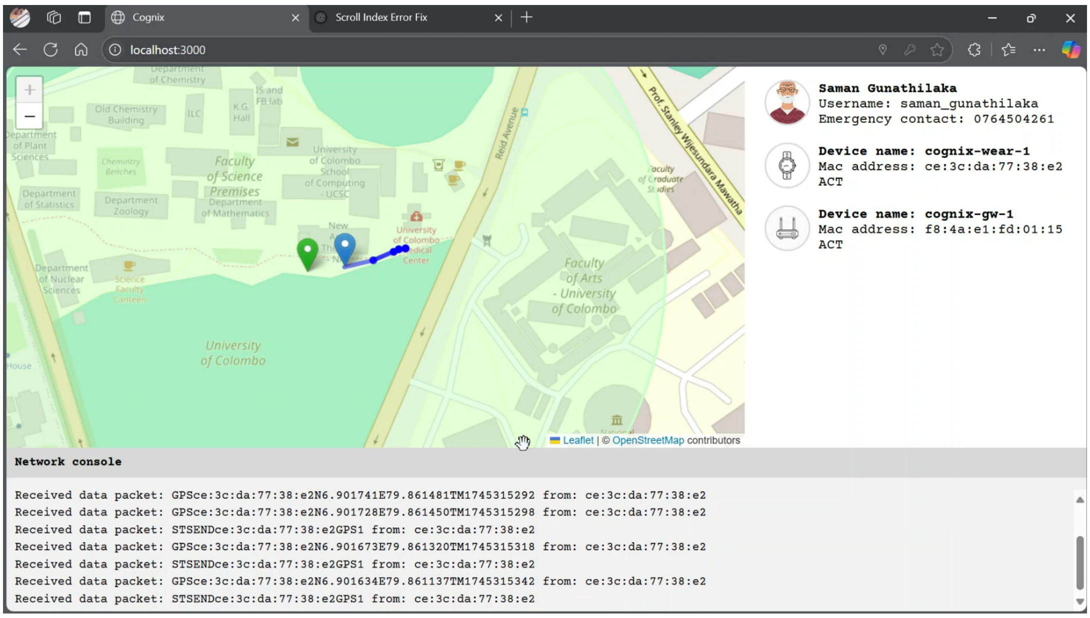

Figure 29: Experiment - Web application interface - 2

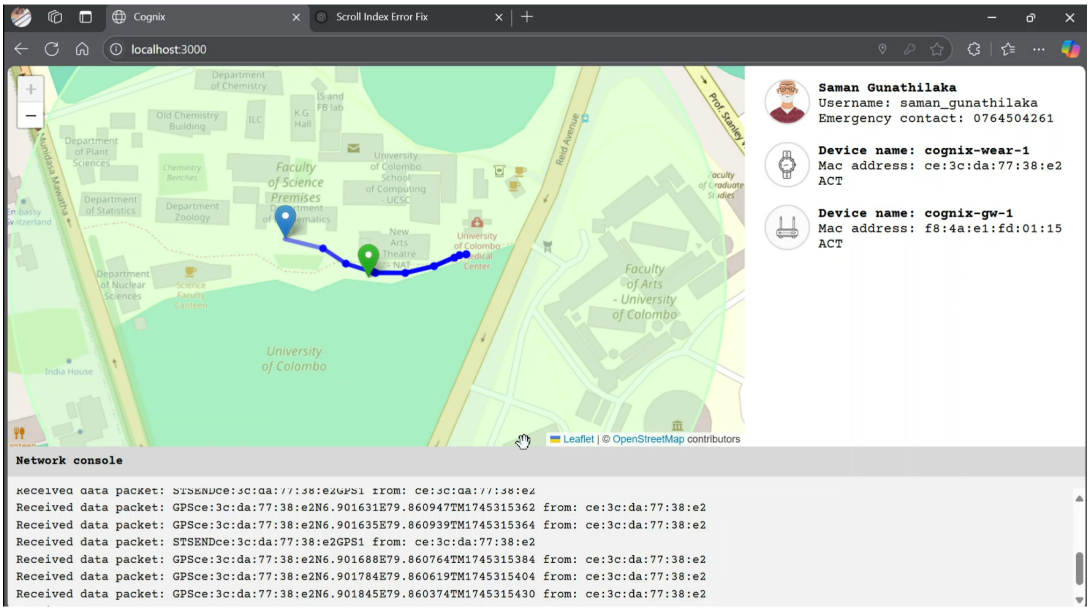

Figure 30: Experiment - Web application interface - 3

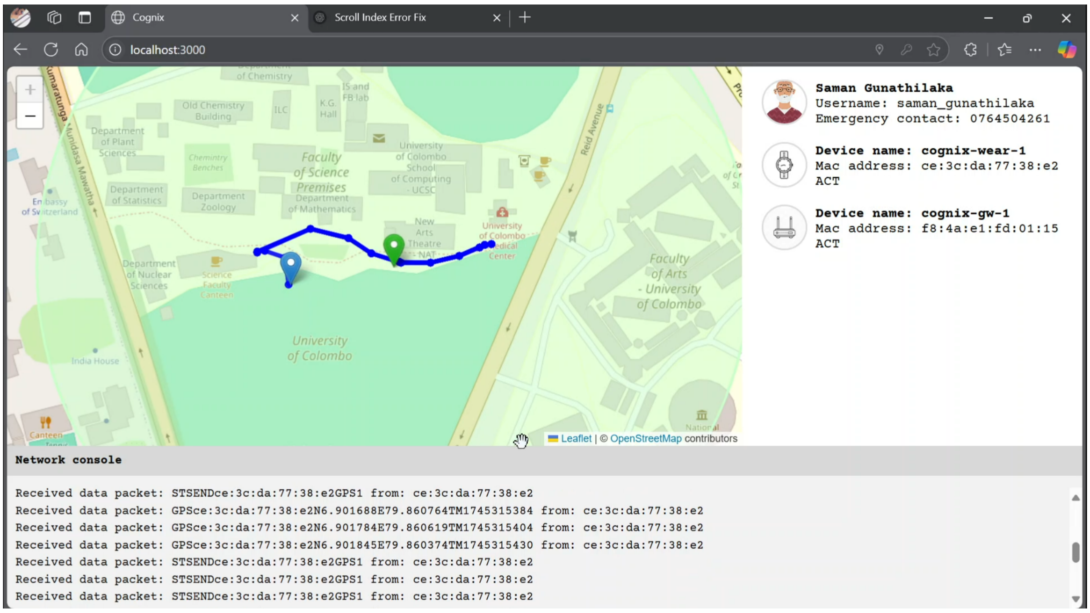

Figure 31: Experiment - Web application interface - 4

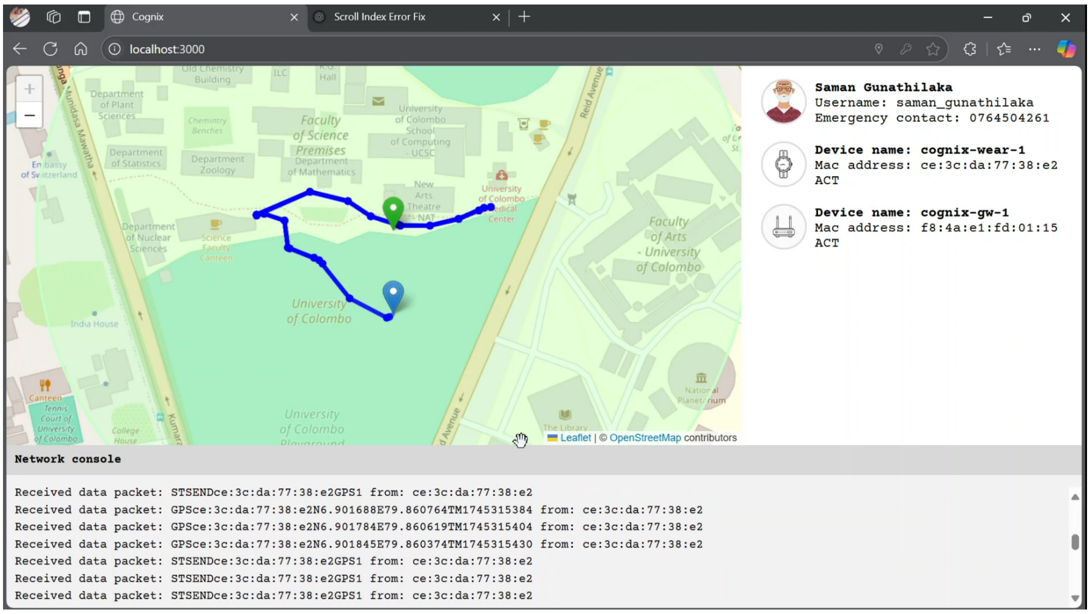

Figure 32: Experiment - Web application interface - 5

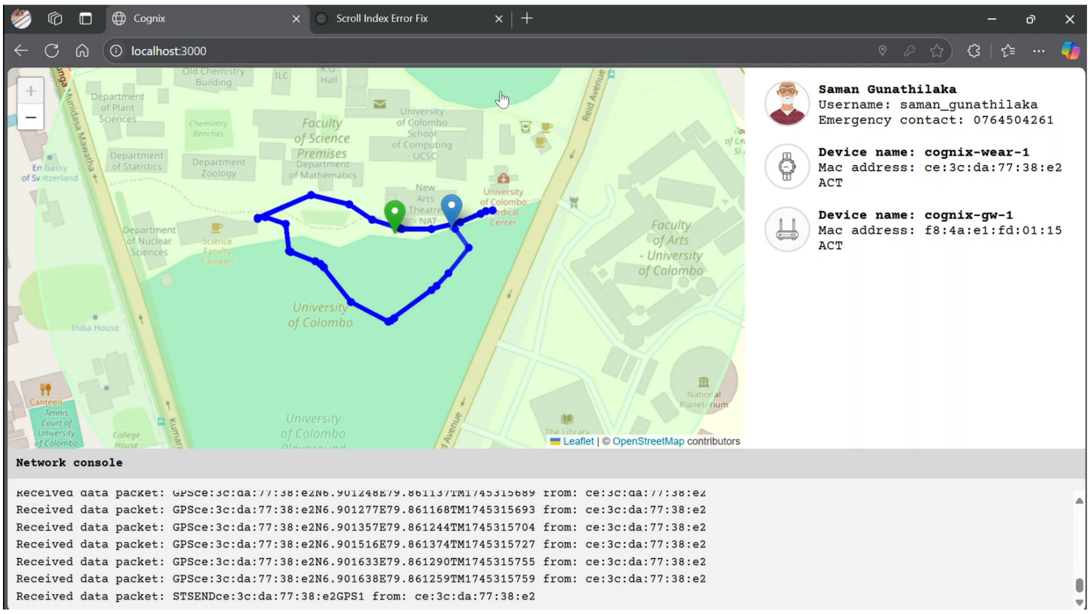

Figure 33: Experiment - Web application interface - 6

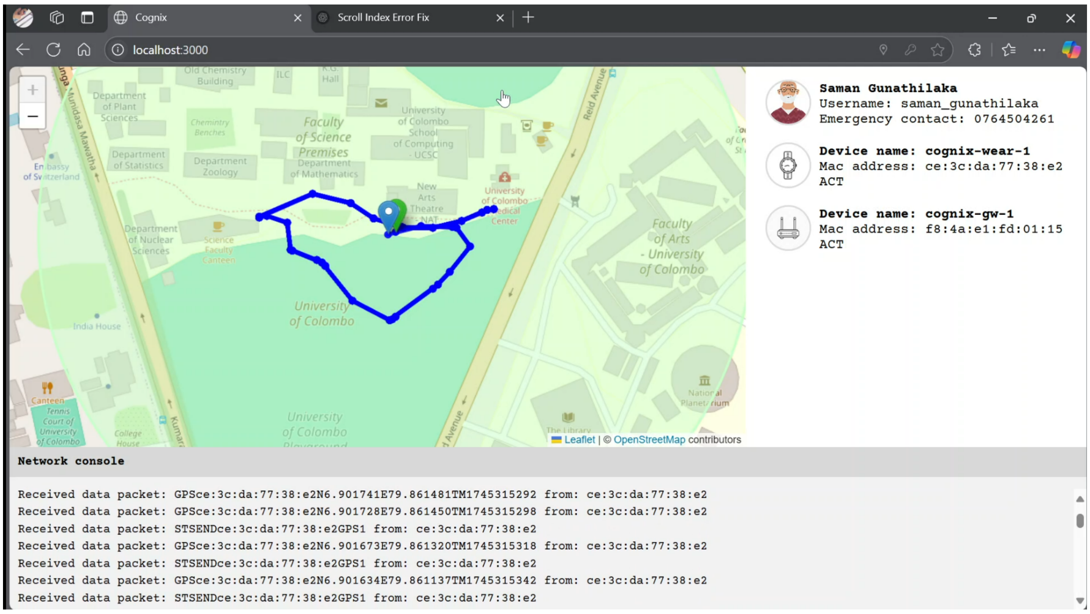

Figure 34: Experiment - Web application interface - 7

```
messageType,nodeType,sourceMAC,gpsStatus,rawData,utcTimestamp,latNS,latVal,longWE,longVal,beReceivedTime
STS,END,ce:3c:da:77:38:e2,1,STSENDce:3c:da:77:38:e2GPS1,,,,,,,1744106660289
GPS,END,ce:3c:da:77:38:e2,,GPSce:3c:da:77:38:e2N6.901756E79.861694TM1744106653,1744106653,N,6.901756,E,79.861694,1744106665690
GPS,END,ce:3c:da:77:38:e2,,GPSce:3c:da:77:38:e2N6.901756E79.861694TM1744106653,1744106653,N,6.901756,E,79.861694,1744106671269
GPS,END,ce:3c:da:77:38:e2,,GPSce:3c:da:77:38:e2N6.901790E79.861755TM1744106667,1744106667,N,6.901790,E,79.861755,1744106676953
GPS,END,ce:3c:da:77:38:e2,,GPSce:3c:da:77:38:e2N6.901793E79.861755TM1744106673,1744106673,N,6.901793,E,79.861755,1744106682486
GPS,END,ce:3c:da:77:38:e2,,GPSce:3c:da:77:38:e2N6.901793E79.861755TM1744106673,1744106673,N,6.901793,E,79.861755,1744106688099
STS,END,ce:3c:da:77:38:e2,1,STSENDce:3c:da:77:38:e2GPS1,,,,,,,1744106691324
GPS,END,ce:3c:da:77:38:e2,,GPSce:3c:da:77:38:e2N6.901786E79.861778TM1744106684,1744106684,N,6.901786,E,79.861778,1744106696678
GPS,END,ce:3c:da:77:38:e2,,GPSce:3c:da:77:38:e2N6.901786E79.861778TM1744106684,1744106684,N,6.901786,E,79.861778,1744106702292
```

Listing 7: Message Data

```
Statistics for duration_s:
count    82.000000
mean      2.470841
std       1.168260
min       1.069000
25%       1.797750
50%       2.092000
75%       2.385250
max       6.509000
Name: duration_s, dtype: float64

Mean Duration (in seconds): 2.4708414658414637
Standard Deviation of Duration (in seconds): 1.1682600686762479
Earliest Duration (in seconds): 1.069000006
Latest Duration (in seconds): 6.509000063
```

Listing 8: Packet delivery time statistics

From the test scenario, 82 data entries were collected using GPS location, GPS-generated time (utcTimestamp), and received timestamp(beReceivedTime) from the web server after being transmitted and processed by the gateway through the LoRa medium. According to the pre-processed data, the average latency for a data packet is 2.470841 seconds(above listing), and the system can provide the location of the dementia every 2.5 seconds. This latency can be improved by using better LoRa hardware modules, antennas, and the physical location of the home device.

4.2 Dynamic Geo-fencing Using ML

To show how well the geofencing and zone classification system works, several images are used based on real GPS data. These images show both fixed zones and how the patient moves in real time. In the maps, red areas mean danger zones, yellow areas are warning zones, and green areas are safe zones. These zones are based on land type, terrain, and past behavior. The model's predictions about possible wandering are shown in purple shapes, which highlight areas where wandering might happen. The patient's movement path is also shown using colored lines—red, yellow, or blue—based on how risky each part of the path is. Together, these visual elements help caregivers and researchers understand where it is safe or dangerous for the patient and how well the system predicts wandering behavior.

4.2.1 Experiment 1: Urban Zone with Dense Buildings

```
Timestamp,Latitude,Longitude
09:00:00+00:00,6.90154,79.86054
09:00:01+00:00,6.90154,79.86056
09:00:02+00:00,6.90156,79.8606
09:00:03+00:00,6.90158,79.86064
09:00:04+00:00,6.9016,79.86067
```

Listing 9: Pre-processed data head - Experiment 1

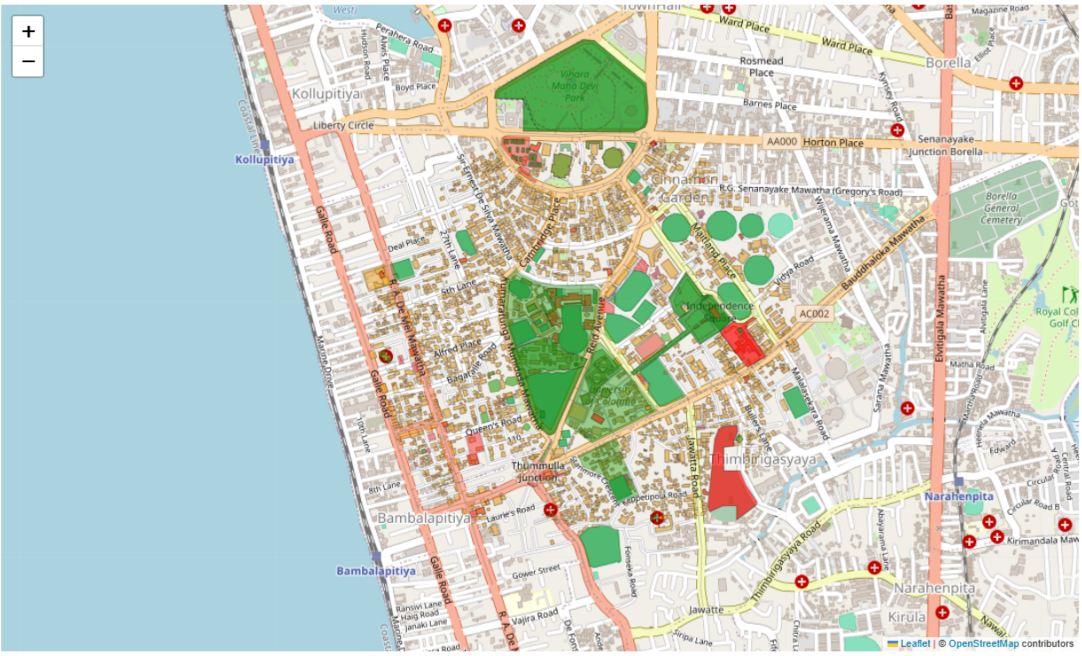

Figure 35: Experiment 1- Zone Classification

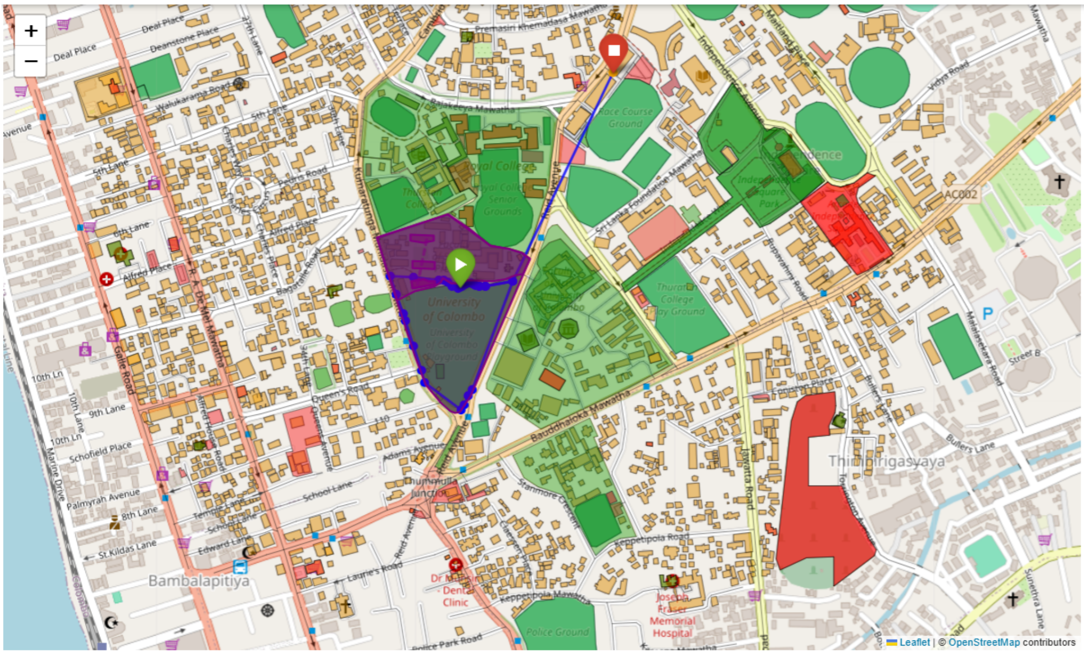

Figure 36: Experiment 1- Wandering Zone Prediction

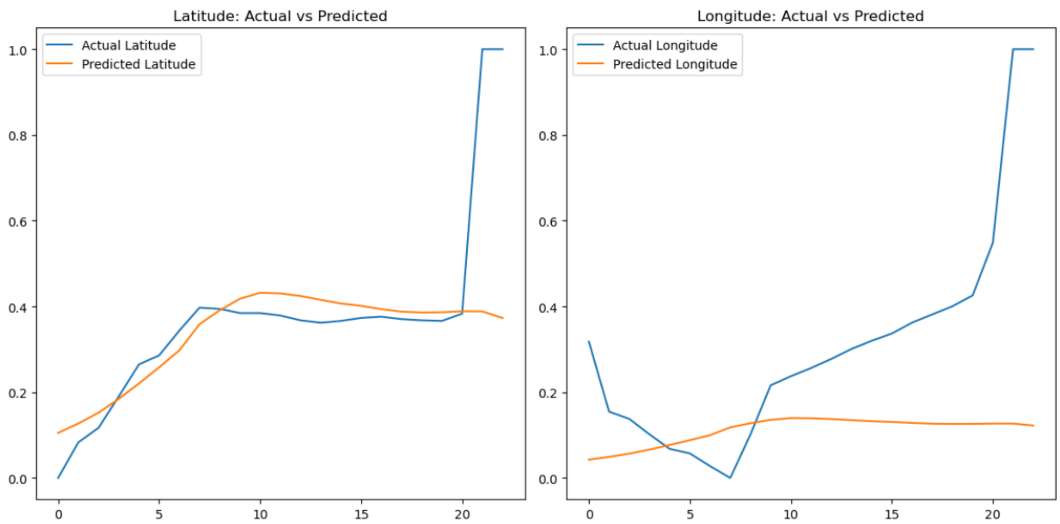

Figure 37: Experiment 1- Evaluation MSE: 0.0467

The predicted coordinates closely match the actual ground truth path, with minimal deviations at sharp turns or signal bounce zones. The error level is acceptable for real-time zone classification and indicates high spatial accuracy.

4.2.2 Experiment 2: Suburban Region near Kandy – Low Movement Variance

```
Timestamp,Latitude,Longitude
```

```
09:00:00+00:00,7.29736,80.65048
09:00:01+00:00,7.29749,80.65043
09:00:02+00:00,7.29761,80.65037
09:00:03+00:00,7.29763,80.65036
09:00:04+00:00,7.29765,80.65036
```

Listing 10: Pre-processed data head - Experiment 2

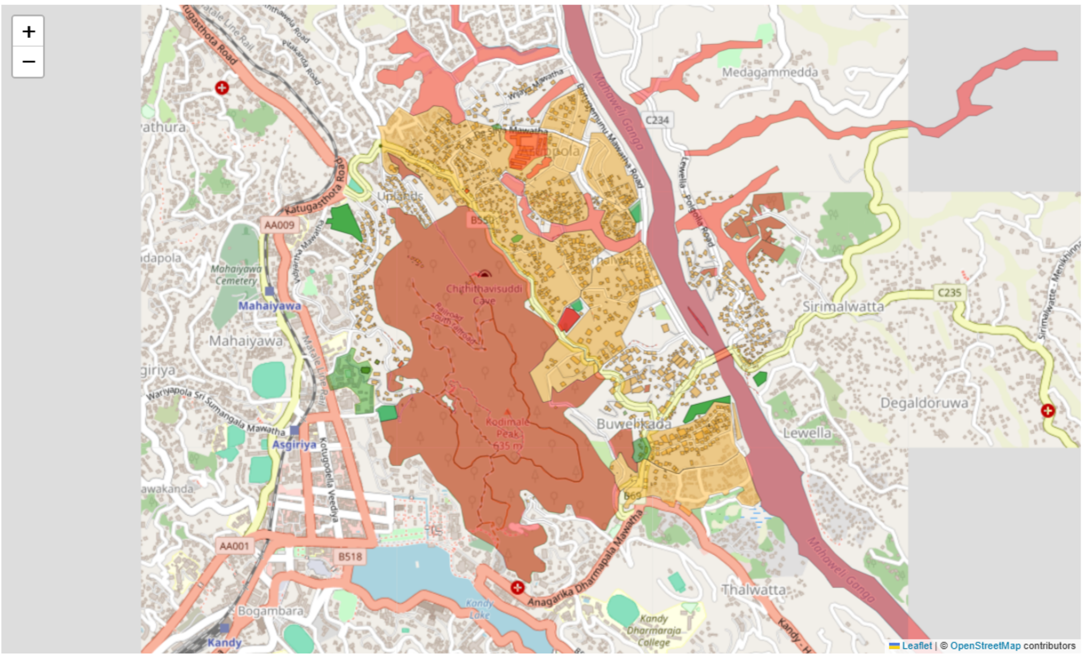

Figure 38: Experiment 2- Zone Classification

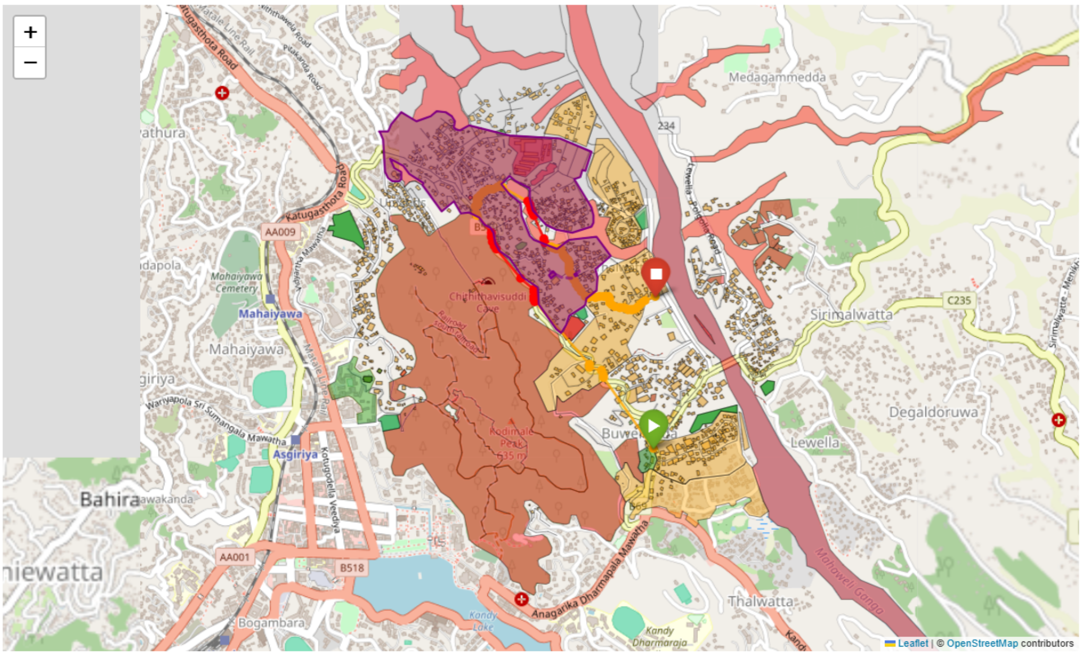

Figure 39: Experiment 2- Wandering Zone Prediction

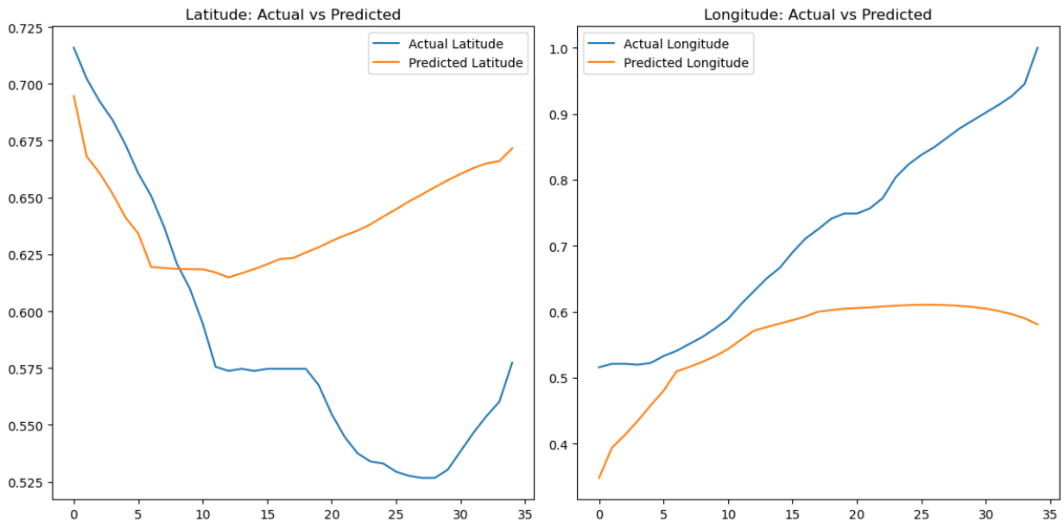

Figure 40: Experiment 2- Evaluation MSE: 0.0189

The model achieved very low error, indicating that in semi-urban or suburban regions like those surrounding Kandy, GPS signals tend to be more stable and easier to learn by the model. The path is mostly linear with slight displacement, resulting in high prediction accuracy. The terrain and lesser signal interference likely contributed to the low MSE.

4.2.3 Experiment 3: Riverbank Area near Kandy – Low-Labeled Terrain

```
Timestamp,Latitude,Longitude
```

```
09:00:00+00:00,7.27409,80.71298
09:00:01+00:00,7.27394,80.71309
09:00:02+00:00,7.27393,80.71309
09:00:03+00:00,7.27362,80.7133
09:00:04+00:00,7.27351,80.71339
```

Listing 11: Pre-processed data head - Experiment 3

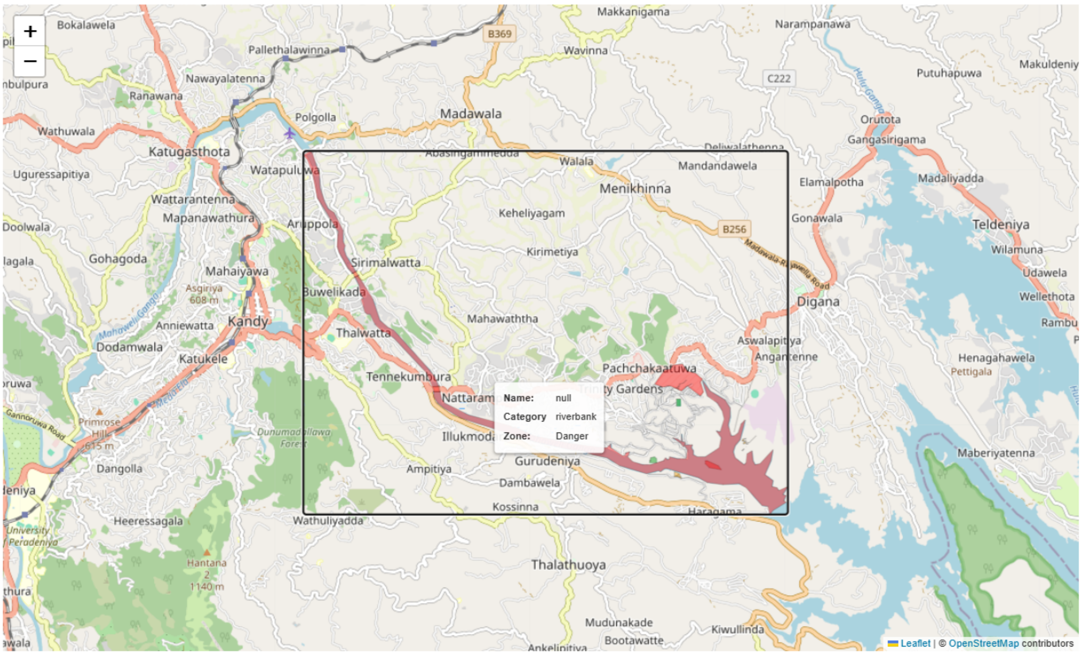

Figure 41: Experiment 3- Zone Classification

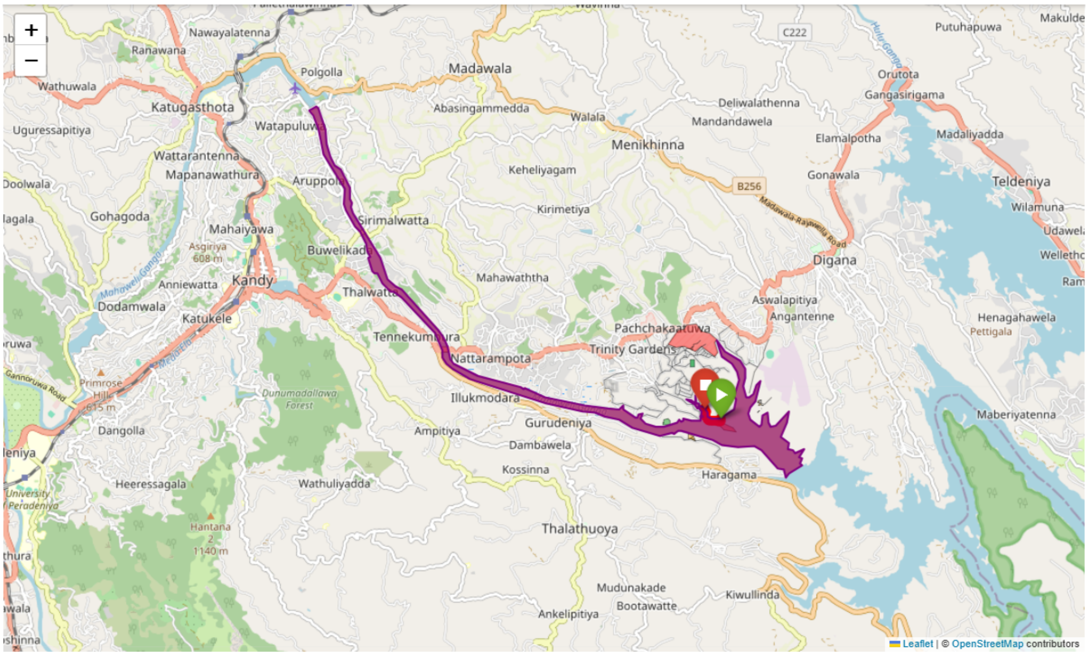

Figure 42: Experiment 3- Wandering Zone Prediction

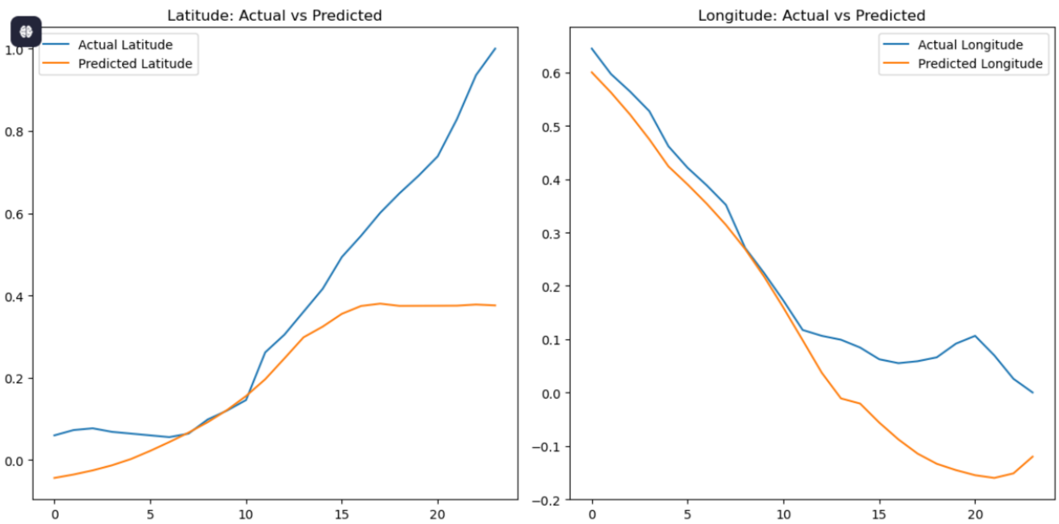

Figure 43: Experiment 3- Evaluation MSE: 0.0263

The model performed with a moderate level of accuracy, as reflected by the MSE. The slight increase in error compared to suburban tests is likely due to the low density of labeled features in this riverbank area, which may reduce the contextual information available to the model. Nonetheless, the path is relatively smooth and consistent, enabling the model to still perform well.

4.2.4 Experiment 4: Nuwara Eliya Golf Club – Familiar Movement Pattern in a Labeled Danger Zone

```
Timestamp,Latitude,Longitude
09:00:00+00:00,6.97396,80.76707
09:00:01+00:00,6.97407,80.76698
09:00:02+00:00,6.9741,80.76695
09:00:03+00:00,6.97419,80.76688
09:00:04+00:00,6.97424,80.76683
```

Listing 12: Pre-processed data head - Experiment 4

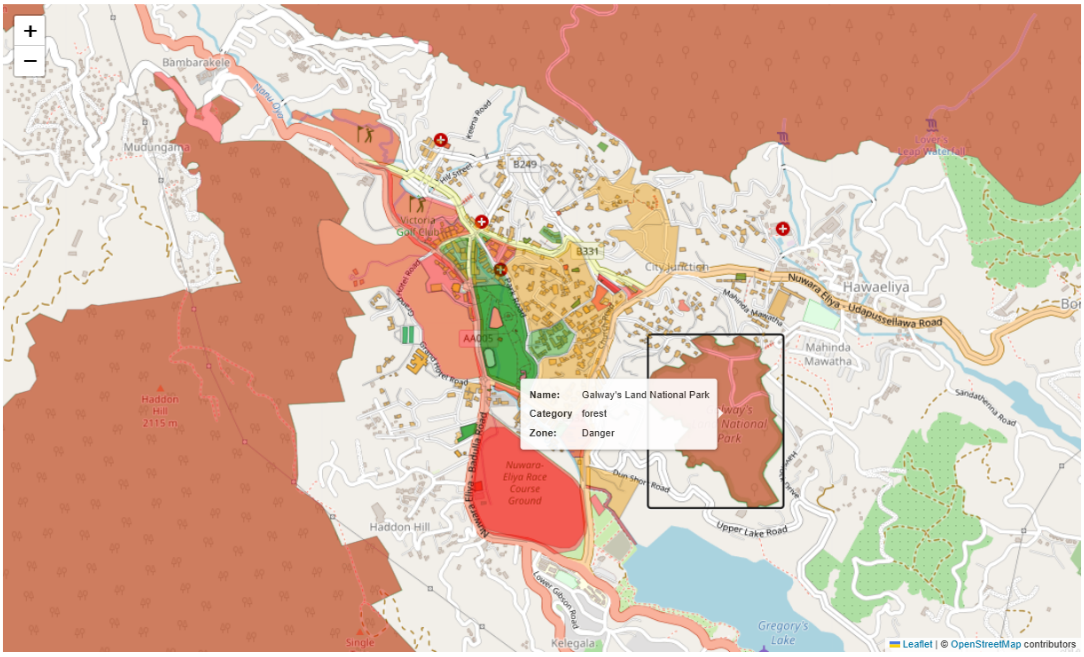

Figure 44: Experiment 4- Zone Classification

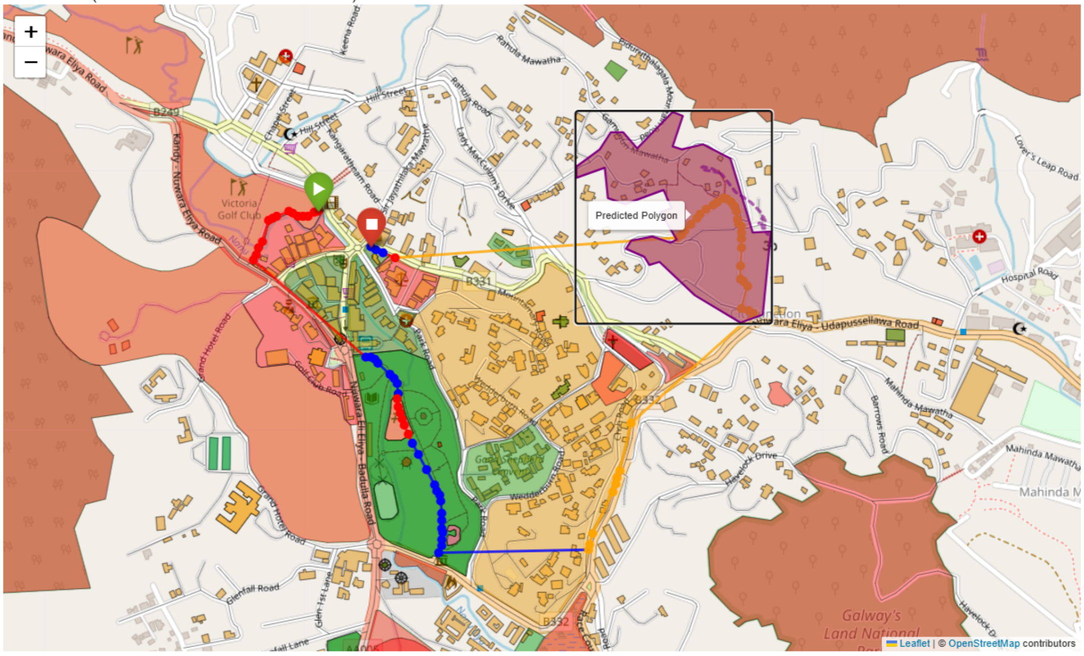

Figure 45: Experiment 4- Wandering Zone Prediction

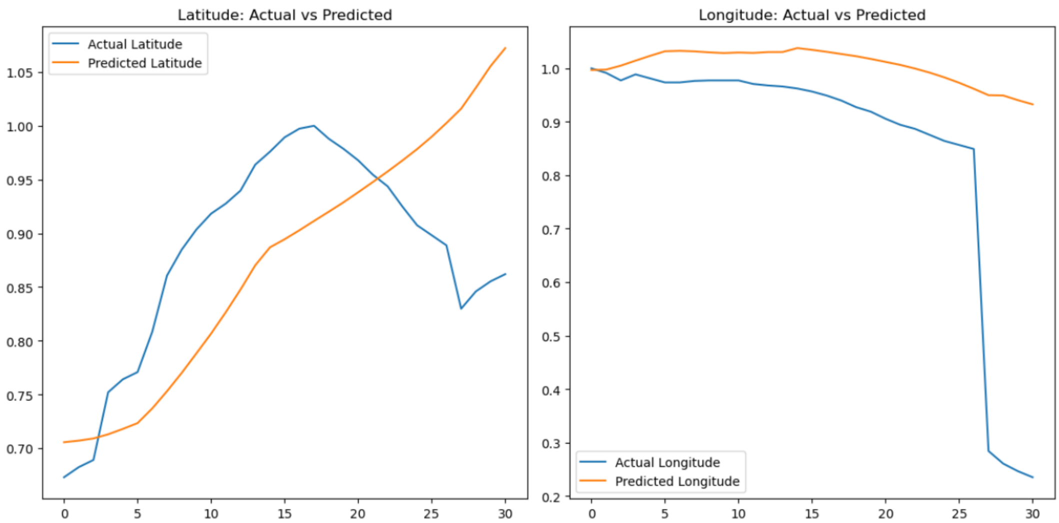

Figure 46: Experiment 4- Evaluation MSE: 0.0382

Despite being labeled as a danger zone, the patient's movement pattern did not exhibit typical signs of wandering. Instead, the movement was smooth, forward-directed, and time-bound, suggesting deliberate navigation rather than aimless roaming. This may reflect the patient's previous experience or comfort with the golf club environment, possibly indicating habitual or recreational use (e.g., golfing).

The model's zone misclassification (from Red to Yellow) is semantically reasonable, as the patient's behavior does not match typical risk patterns, despite the location label.

This implies that behavioral context is as important as geospatial context, especially for adaptive geofencing.

4.2.5 Experiment 5: Rambakan Oya Forest Reservoir – High-Risk Zone with No Path

```
Timestamp,Latitude,Longitude
09:00:00+00:00,7.31104,81.39261
09:00:01+00:00,7.31099,81.39267
09:00:02+00:00,7.31081,81.39292
09:00:03+00:00,7.31144,81.39317
09:00:04+00:00,7.3115,81.39321
```

Listing 13: Pre-processed data head - Experiment 5

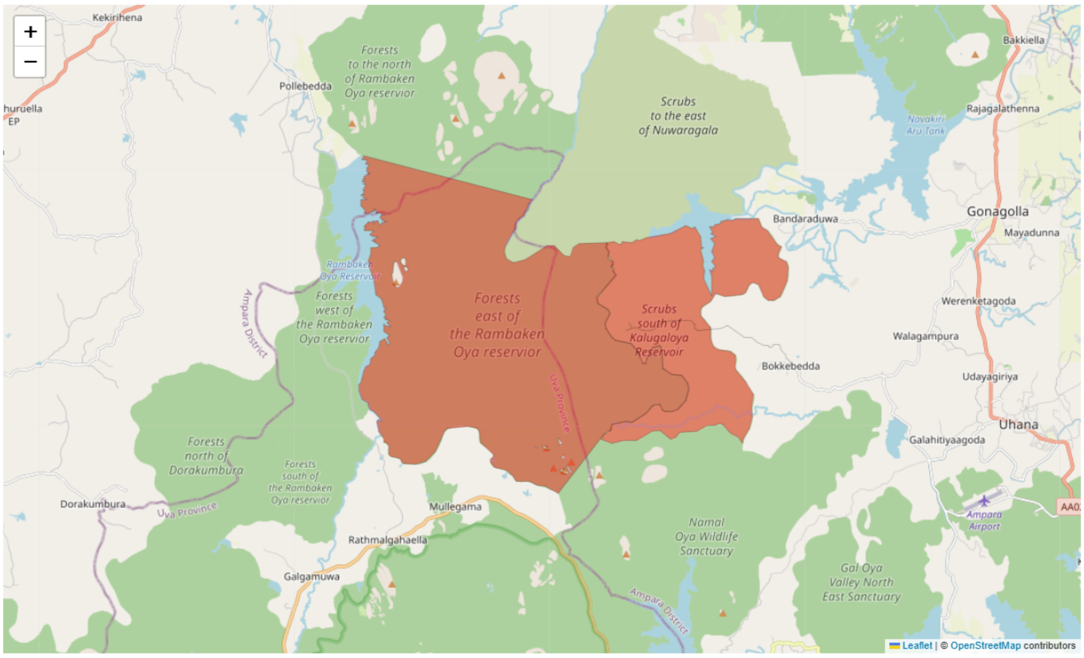

Figure 47: Experiment 5- Zone Classification

The model correctly did not attempt to classify any sub-region as Warning or Safe, reflecting an appropriate risk-averse behavior. The area was fully flagged as dangerous in both ground truth and prediction, showing that the system can prioritize patient safety in clearly hazardous zones. This reinforces the model's reliability in unfamiliar and high-risk terrains, where any movement should trigger immediate alerts.

4.2.6 Experiment 6: Hambantota Coastal Area – Noise Handling and Accurate Wandering Detection

This test is conducted along the Hambantota coastal region, where proximity to large water bodies often introduces GPS drift and location noise. Despite this, the model effectively identified the actual wandering behavior along a nearby residential path, rather than falsely interpreting erratic GPS points near the water as significant.

```
Timestamp,Latitude,Longitude
09:00:00+00:00,6.16415,81.13097
09:00:01+00:00,6.16415,81.13084
09:00:02+00:00,6.16414,81.13016
09:00:03+00:00,6.16415,81.1296
09:00:04+00:00,6.16395,81.1296
```

Listing 14: Pre-processed data head - Experiment 6

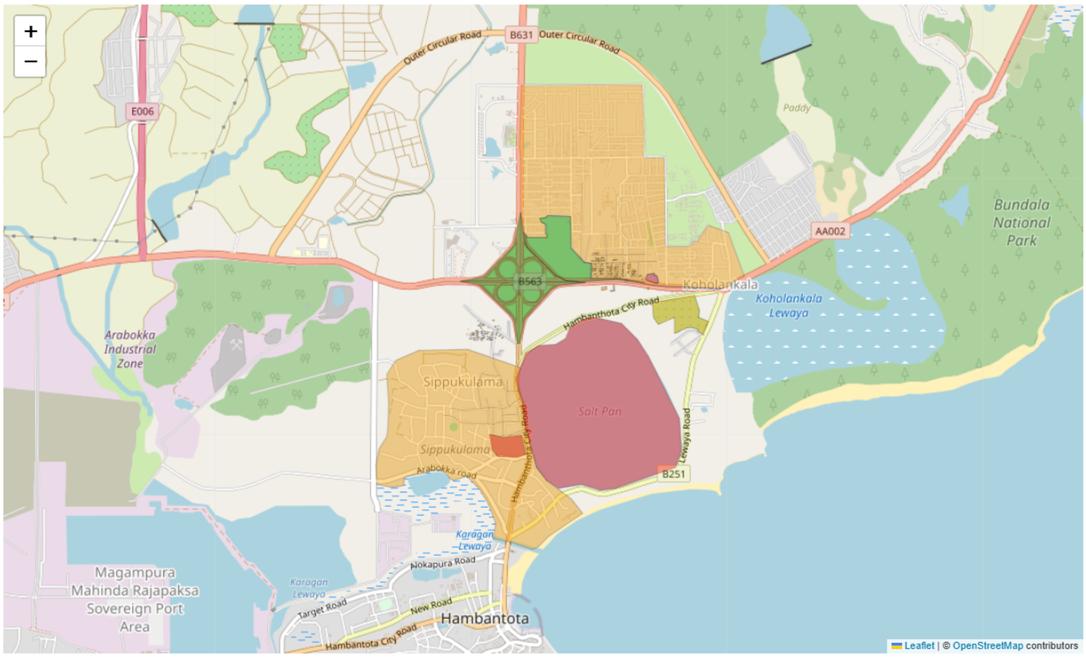

Figure 48: Experiment 6- Zone Classification

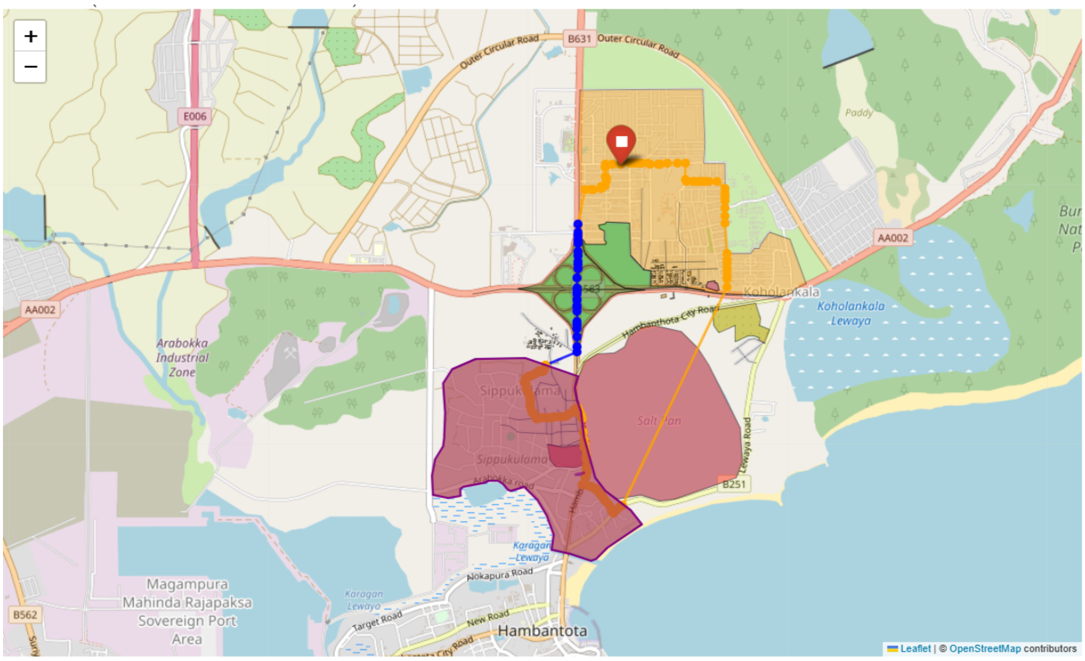

Figure 49: Experiment 6- Wandering Zone Prediction

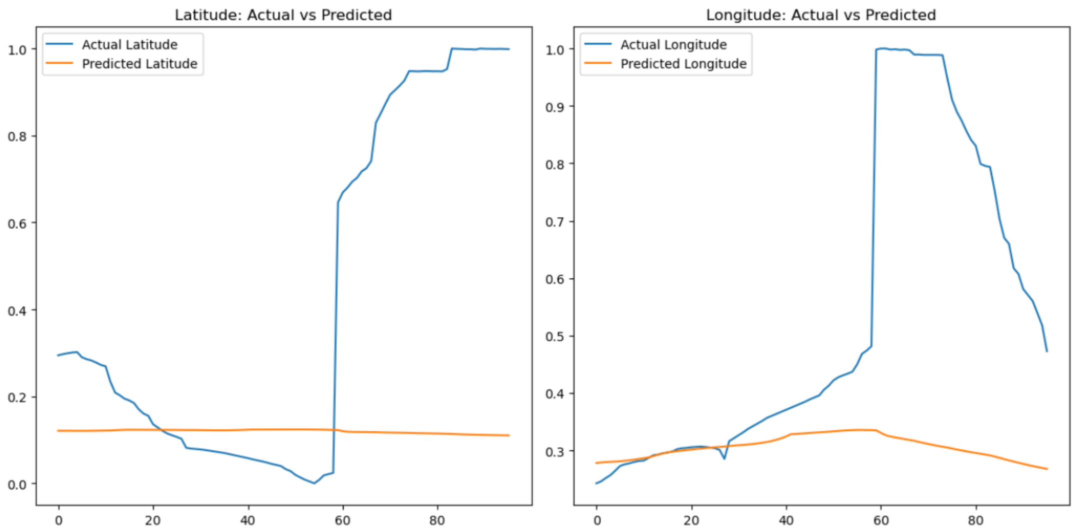

Figure 50: Experiment 6- Evaluation MSE: 0.184

The relatively higher MSE indicates that while the model captured the general wandering behavior, the noisy GPS data from coastal reflection or drift led to misclassification of certain points. This highlights a limitation in handling continuous GPS distortion in open, reflective environments.

4.2.7 Critical Analysis of Dynamic Geo-fencing

The experimental evaluations conducted across geographically and semantically diverse locations—such as the Kandy riverbank, Nuwara Eliya golf club, Rambakan Oya forest reserve, and Hambantota coastal belt—provide a multi-faceted lens through which the system's current strengths and deficiencies are revealed. The machine learning-based geofencing approach, driven by GPS trajectory inputs and spatial metadata (e.g., terrain and land-use types), showed commendable ability in learning spatial behavior patterns rather than relying on static spatial labels. For instance, despite the Nuwara Eliya golf club being labeled as a "danger" zone in the static database, the system learned from sequential GPS data that the movement was routine and bounded, which was reflected in a lower predicted threat level (yellow zone). This reflects an important feature: the model learns from behavior over space, not from static classification, offering contextual intelligence in decision-making.

Additionally, the mean squared error (MSE) across tests remained low in areas with well-defined movement patterns (e.g., near residential roads in Hambantota or through known village paths in Kandy), showcasing the model's competence in trajectory fitting and spatial generalization. However, in less structured environments such as Rambakan Oya forest reserve—where no meaningful trajectory pattern exists—the model rightly identifies the region as entirely dangerous, demonstrating the model's ability to generalize high-risk areas when behavioral data is absent or non-interpretable. That said, this conservative fallback might limit utility in nuanced wilderness tracking, where portions of the area could be relatively safer but are uniformly flagged due to data sparsity.

On the downside, there were several technical bottlenecks. First, GPS noise and sampling gaps in open environments (coastal areas, large fields) introduced trajectory artifacts, leading to increased MSE in some scenarios (e.g., 0.184 in the Hambantota test). This underscores the need for Kalman filtering, dead reckoning, or spatio-temporal smoothing techniques to better estimate true movement paths. Second, the lack of temporal modeling is evident: patients moving at different times of day or under different activity contexts (e.g., exercise, wandering, leisure) are not differentiated. This severely limits the model's behavioral context awareness, especially in recurring-use zones like golf clubs. Integrating time-windowed modeling (using LSTM or Transformer-based sequence learning) would allow the system to build richer embeddings of "routine vs anomalous" behavior over time.

Furthermore, the model currently treats all terrain classes equally in behavioral modeling, even though terrains (e.g., forest, water, commercial areas) have asymmetric risk implications. In future iterations, introducing risk-weighted terrain encoding, multi-modal sensor fusion (e.g., movement from accelerometer, heart rate anomalies), and personal behavior profiling (e.g., known safe patterns for the patient) would significantly improve prediction robustness. Additionally, the model could benefit from adaptive zoning, where zones are dynamically adjusted based on recent behavior history and environmental conditions (e.g., weather, local events).

In summary, while the current implementation demonstrates strong foundational capabilities in spatial movement interpretation, its evolution demands attention to signal robustness, temporal intelligence, and behavioral personalization. Such enhancements will not only improve precision but also elevate the clinical utility and caregiver trust in the system for real-time dementia patient monitoring and intervention.

4.3 Multisensor-Based Off-Body Detection

4.3.1 Using TTP223 capacitive touch sensor

During the controlled testing the TTP223 capacitive touch sensor showed excellent sensitivity in identifying direct skin contact. Eventhough there was a small distance of 2 mm between the sensor and the skin, it reliably and precisely registered touch which proved its ability to record both firm and gentle touch inputs. However the sensor demonstrated a notable tendency for false positive throughout prolonged testing across a range of real world materials and surfaces. The sensor frequently misidentified objects like metals, plastic or wood as legitimate touch events when the device was placed on them. Similarly the sensor continued to record touch events even when it was covered with materials like cloth or glass and then touched by a hand or object.

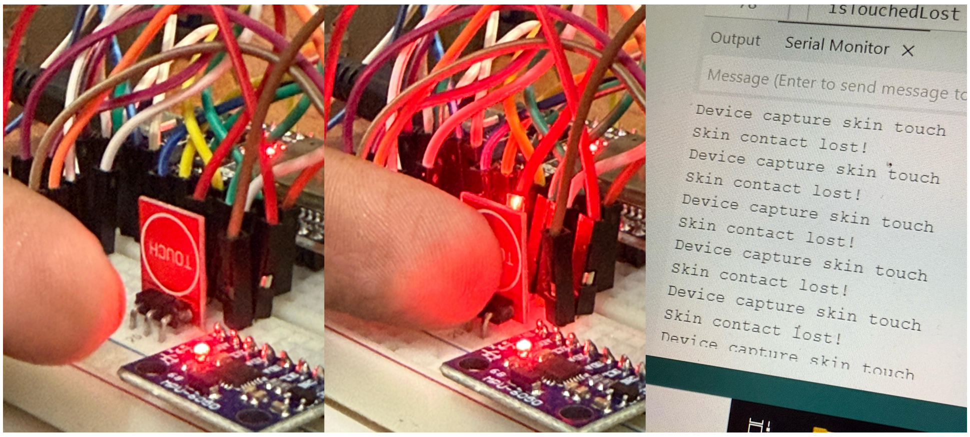

Figure 51: TTP223 Touch Test

These findings suggest that although the TTP223 is highly effective at instantly identifying skin like touch it is not able to discriminate between conductive or semi conductive non skin materials and real skin. It is unreliable as a stand alone sensor for off body detection because of its restrictions. Consequently it is clear that this sensor needs to be combined with other methods like motion sensing or bioimpedance in order to correctly detect real skin contact and ascertain if the device is being worn or taken off.

4.3.2 Using MPU6050 Motion Sensor

When the gadget was worn the MPU6050 motion sensor successfully recorded quite motion patterns. The sensor displayed constant and dynamic changes in acceleration and orientation when being used actively such as when walking moving hands or moving the body in general. Due to physiological micro movements it is continued to register slight variations even when it was in low activity states such as sleeping or sitting motionless. But there was also a detectable level of noise in the raw sensor data particularly in static or low motion situations. This was fixed by adding a motion detection threshold to the accelerometer's X, Y, and Z axes. The threshold was adjusted to remove noise and better capture real motion through a series of tests involving movements in various directions and speeds. With the use of this threshold mechanism detection was greatly enhanced enabling the system to reliably detect movements and accurately determine when the gadget became stationary.

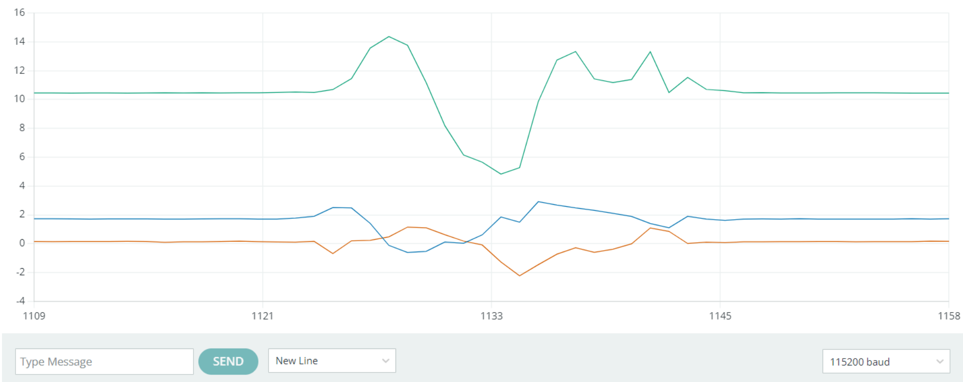

Figure 52: Acceleration Plot

```
Acceleration X: 1.92, Y: -0.19, Z: 10.89 m/s^2
Rotation X: -0.07, Y: -0.10, Z: -0.12 rad/s

Acceleration X: -2.88, Y: 3.68, Z: 9.11 m/s^2
Rotation X: -0.94, Y: -0.14, Z: 0.41 rad/s

Acceleration X: 5.09, Y: 1.44, Z: 12.50 m/s^2
Rotation X: 0.79, Y: 0.61, Z: -0.53 rad/s
```

Figure 53: Acceleration Gyroscope value

These findings demonstrate how well the MPU6050 detects if the device is being worn actively as opposed to being taken off or left unattended. The accelerometer and gyroscope readings stabilised, indicating a static state when the gadget was taken out and set on a table or other surfaces. The sensor only detected short erratic bursts of motion if the gadget was in a pocket or bag without being worn; it did not detect the steady movement profile that a worn device would have. This will cause the person to continue carrying the device or to dress without wearing it. One important factor in lowering false positives brought on by sensor noise was the threshold mechanism. Taken into account even if MPU6050 by itself cannot verify skin contact, it provides vital motion based indications like orientation changes and motion cessation that when paired with information from the capacitive and bioimpedance sensors, allow for a dependable and complete off body detection system.

4.3.3 Using MAX30102 bioimpedance sensor

When the MAX30102 optical sensor was pressed firmly against human skin, it was able to generate reliable and consistent photoplethysmographic (PPG) waveforms. It was able to capture rhythmic signal patterns that closely mirrored the user's pulse while being tested on the wrists and fingertips, which indicated that the presence of living tissue. It's interesting to note that some infrared values persisted even when the sensor was not in contact with the skin or was lying on materials like wood, plastic, or metal. However, the periodic, pulse-like waveform observed during real human touch was absent from these observations. Rather, they exhibited a lack of biological rhythm and flat or uneven patterns. As a result, human skin contact can be differentiated from false positives by examining the IR signal's pattern and structure rather than just its existence.

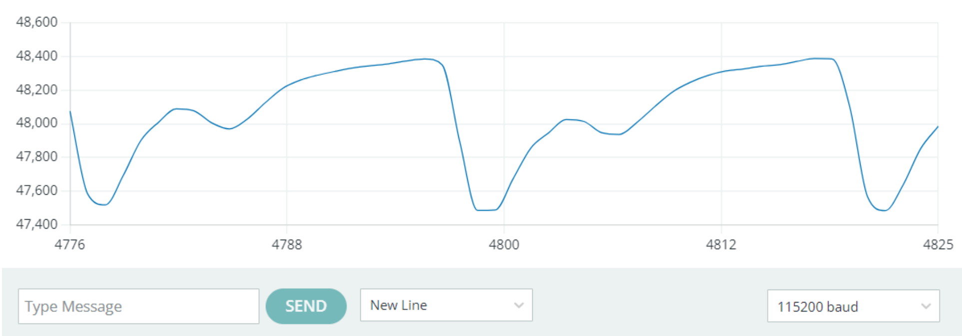

Figure 54: Finger Tip Touch

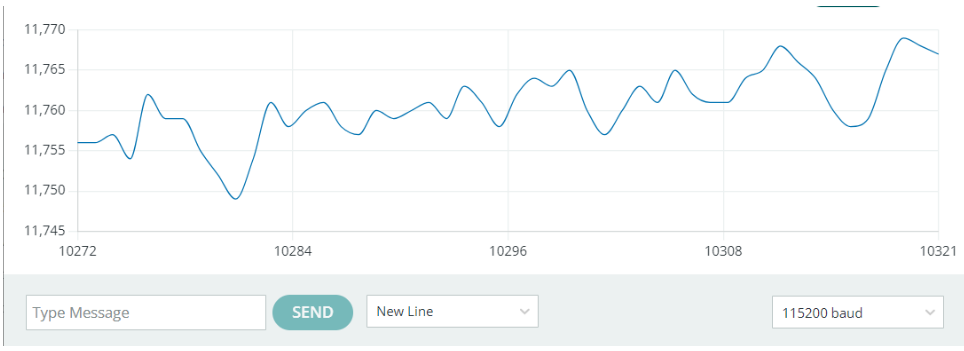

Figure 55: Metal Surface Touch

Figure 56: Plastic Surface Touch

One of the MAX30102's main advantages is its ability to distinguish between legitimate human interaction and object interference. No non-living surface can completely reproduce the biological reflectance qualities that the sensor uses. The dynamic, pulsating waveform that is specific to blood flow is not produced by metal or plastic, despite the fact that they may reflect infrared light and produce some raw data. This enables the detection of real human presence not only by signal strength but also by waveform features. However, if the contact is too loose or blocked by clothing, the PPG signal may deteriorate or vanish, impairing the accuracy of the sensor. Therefore, when it comes to confirming human skin contact, the MAX30102 is quite trustworthy.

4.3.4 Using All three sensor

By examining touch continuity, motion patterns, and biometric data, the system can precisely determine if the device has been withdrawn from the user's body, regardless of how firm or minimal the contact was, due to the combined logic of all three sensors.

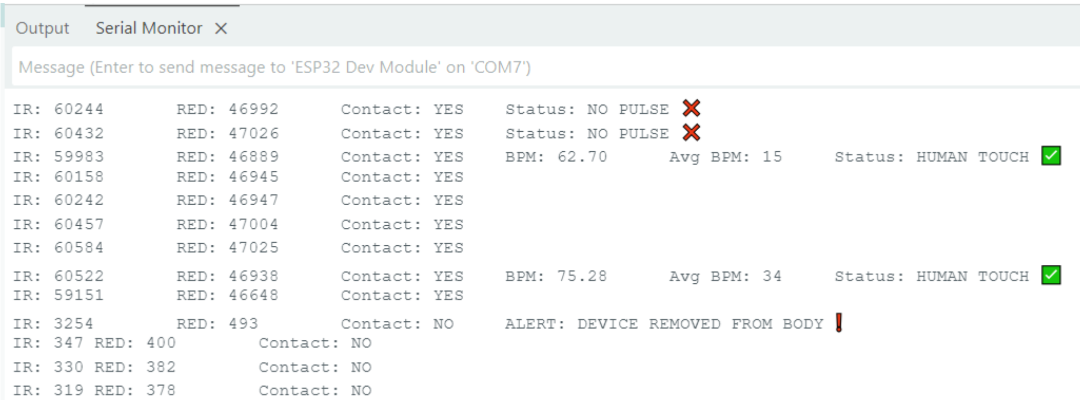

Figure 57: Tightly touched device remove detection

Figure 58: Lightly touched device remove detection

4.4 Device Placement Based on Sensor Performance

The area of the body where the device is worn has a significant impact on how well off-body detection and physiological monitoring utilizing the MAX30102 and MPU6050 sensors work. With an emphasis on the quality of the heart rate signal (IR value from MAX30102) and movement patterns (acceleration in X, Y, Z axes from MPU6050), an assessment was thus carried out to examine the performance of both sensors across various body positions.

Wearables are frequently and conveniently placed on the wrist. According to tests, the MAX30102 sensor provided reliable and accurate pulse waveforms along with powerful infrared signals at the wrist. Both skin contact and heart rate were successfully detected by the sensor. However, frequent hand movements, such eating, waving, or adjusting clothes, caused the MPU6050 to provide high-magnitude acceleration values across all axes. Although these data demonstrate strong motion sensitivity, they also add noise, which raises the possibility of off-body detection erroneous triggers. As a result, the wrist is ideal for tracking heart rate, albeit software may need motion filtering to increase precision.

One of the finest locations for both sensors was the chest region. Because of its closeness to the heart and the lack of interference from significant movements, the MAX30102 generated steady infrared signals with a distinct heart rate pattern. Furthermore, the MPU6050 consistently recorded low to moderate motion data, particularly when the individual was seated, walking, or changing between tasks. The chest region was shown to be less susceptible to motion noise, which makes it a perfect place for both accurate off-body detection and physiological monitoring.

Additionally, placement on the upper arm produced positive outcomes. Due to sporadic variances in skin contact, the MAX30102 IR signal was not as strong as the wrist or chest, but it was still generally powerful. In comparison to the wrist, the MPU6050 recorded mild acceleration patterns that efficiently captured overall arm motion with less noise. Because of this balance, the upper arm is a viable substitute location, particularly if the chest region is uncomfortable or inaccessible for extended use.

On the other hand, the MPU6050 sensor performed exceptionally well in the waist and hip areas. These points gave balanced, steady motion readings with distinct transitions between walking and stillness because they are close to the body's center of gravity.

However, because of the thicker skin and lower capillary density in these areas, the MAX30102 had trouble picking up strong infrared signals, and the pulse waveforms were weak or irregular. Therefore, these locations are better suited for motion tracking than for bio-signal monitoring.

Good motion sensitivity was offered by the ankle, particularly when walking. With minimal noise, the MPU6050 recorded repeating and rhythmic acceleration patterns. However, the ankle's MAX30102 readings were feeble and wildly erratic, most likely as a result of irregular sensor contact and restricted blood flow. Because of this, the ankle works well for monitoring steps or analyzing overall movement, but not for precisely detecting heart rate or human presence.

Lastly, the findings varied depending on whether the collar or neck was placed. Although MAX30102 occasionally captured powerful infrared signals, movement or garment interference frequently interfered with readings. The neck usually stays still when walking, hence the MPU6050 also captured very little movement. This positioning is inconsistent and could not be dependable for motion detection or heart rate monitoring.

In summary, the chest proves to be the most dependable and efficient place to affix the device, providing excellent readings for both sensors. The wrist and upper arm are good substitutes for the chest if it is not feasible, especially when signal processing is done correctly. Although regions such as the waist or ankle provide precise motion tracking, they are not advised as the main locations for off-body detection devices in dementia care since they are less suited for physiological sensing

5 Discussion and Conclusion

The main goal of using LoRa as a communication medium is to reduce costs for wearable devices and to create devices that are more energy efficient compared to other communication mediums, including cellular. Even though the prototype LoRa module can cover a radius of up to 300-400 meters, there are multiple physical factors that affect packet delivery. The placement of the antenna and the power of the LoRa module are crucial factors, especially when utilizing industrial-grade LoRa modules that can achieve a range of up to 10 kilometers. According to the results of the experiments, data packet delivery experiences a latency of about 1.5 to 2 seconds maximum, from the LoRa wearable device to the web application, with intermediate processing in the home device node. Given the walking speed of elderly dementia patients, it's better to monitor their movement in neighborhoods and crowded areas. The wearable device is a cost-effective option, priced at less than Rs. 7,000, while home devices are approximately Rs. 4,000. Compared to other mediums, LoRa is energy-efficient, which makes it a good option for long-term use without changing batteries.

With the proposed protocol, the coverage area can be extended in the future, since the number of home devices is equal to the number of wearable devices, which helps provide better performance in urban areas. The developed web application is user-friendly, and caregivers can easily track their loved ones in real-time.

This research presents a machine learning-driven geofencing system capable of classifying spatial zones and predicting wandering behavior in dementia patients using GPS movement data and regional geographic features. The integration of land use patterns, terrain information, and sequential GPS traces enabled a dynamic approach to zone classification, moving beyond static radius-based geofencing. Experimental results conducted across diverse terrains demonstrate the system's capacity to distinguish between routine and abnormal movement patterns.

The Mean Squared Error (MSE) observed across test cases remained within acceptable thresholds, confirming that the model consistently predicts wandering behavior with spatial accuracy. Notably, the system successfully identified typical behavioral patterns in familiar regions such as golf clubs or residential areas, while raising warnings in less safe environments such as forest reserves or isolated coastal paths. These results highlight both the sensitivity and contextual adaptability of the model.

However, certain limitations emerged. The accuracy of predictions is partially constrained by the granularity of shapefile data and the quality of GPS inputs. Noise in data, such as jitter or inaccurate GPS sampling, can occasionally lead to misclassifications, especially in transitional zones between terrain types. Additionally, the current model is based on generalized behavior, which may not capture the nuances of individual patient routines.

Advanced tracking, real-time monitoring, and alert systems are essential components of wearables for dementia care, but their efficacy depends solely on the patient actually wearing the device. All monitoring features stop working if the wearable is taken off, whether on purpose or by mistake, which could endanger the patient. The dependability of current systems is severely constrained by this difficulty, particularly in unsupervised settings.

This crucial deficiency is directly filled by integrating a strong off-body detecting method. The system continuously confirms that the gadget is in physical contact with the patient by integrating biometric verification, motion tracking, and capacitive touch sensing. This function boosts caregiver confidence in addition to improving the system's safety and dependability. Caregivers can give dementia patients greater freedom and movement because they know the device will alert them automatically if it is removed or not working as intended. This makes the caregiving atmosphere more empathetic, lessens the burden of constant supervision, and gives caregivers the confidence to trust the technology.

6 Future Directions

The prototype and experiments conducted using the LoRa Ra-02 SX1278, which is a basic LoRa module available on the market, and using improved industrial-grade LoRa modules, will improve the latency and coverage of the devices. Developing a custom PCB board will drastically reduce the size of the wearable device and can be customized for different types of wearable devices, including watches, belts, and attachments to patient care equipment like walkers. Wearable devices and home devices can be further extended to track the indoor movements of dementia patients, which can be used to detect emergency situations.

Home devices can further extend to include voice assistance, such as Amazon Alexa or Google Assistant, to provide conversational-based monitoring of patients in indoor situations, helping them with day-to-day activities.

To further improve the reliability and contextual intelligence of the proposed geofencing and zone classification system, future work can focus on personalized behavioral modeling. By maintaining a temporal history of each patient's unique movement habits—such as preferred routes, daily routines, or seasonal behavior shifts—the system can shift from generalized risk detection to individualized anomaly detection. Incorporating sequence modeling techniques like Transformer-based architectures could allow the system to learn long-term dependencies in a patient's movement and better detect deviations from their norm.

In addition, spatiotemporal risk fusion can be introduced, where zone classification is enriched by combining terrain data with live environmental feeds—such as weather conditions, event-based crowd data, or traffic reports. This could be particularly useful for distinguishing between static geographic risks and temporary situational hazards (e.g., a road under construction or a sudden flood risk). Integrating such real-time feeds can make the system more adaptive to real-world changes.

Another powerful direction involves semi-supervised learning for zone boundary refinement. Many regions, especially rural or forested areas, lack high-quality labeled data for training. By using a small set of expert-verified zones and large volumes of unlabeled movement traces, the model can self-improve using cluster-based or contrastive learning approaches, allowing for scalable deployment in new geographic regions with minimal manual labeling effort.

Lastly, incorporating a caregiver feedback loop—where manual corrections or observations from caregivers are used to update or fine-tune model predictions—can turn the system into a continuously learning platform. This human-in-the-loop architecture would not only enhance accuracy over time but also build trust and transparency in real-world caregiving environments.

Machine Learning-Based Sensor Fusion is one of the upcoming improvements for the off-body detection system. The system currently uses rule-based logic, but in order to better fuse sensor data, machine learning methods like neural networks or decision trees could be useful. In addition to forecasting possible health hazards based on continuous sensor data, this would enable the system to learn from real-world usage, adjust to individual behaviors, and decrease false positives or negatives.

Another area that needs work is adaptive threshold calibration. Sensor accuracy can be impacted by variables such skin type, environment, and device positioning. Dynamic thresholding would allow the system to adapt its sensitivity over time to preserve accuracy while taking the user's body or surroundings into consideration. The system can be improved even more by integrating health monitoring. The device may provide continuous health monitoring by measuring temperature, heart rate, and SpO2. It can also notify caregivers of any significant changes, including a sudden drop in heart rate, which enables them to respond to possible crises more quickly.

Lastly, by estimating the patient's position in relation to the last known GPS location using data from the MPU6050 sensor, Position Tracking During GPS Signal Loss can be enhanced. The method could improve overall safety by tracking the patient even in situations where GPS signals are lost by examining movement patterns

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