



Real-Time Frailty Detection for Elderly Care in Indoor Environments

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ABSTRACT

The rapid growth of the global older population has become a major public health concern, placing increasing pressure on healthcare systems to address age-related health condition effectively. Frailty syndrome is an age-related condition characterized by increased vulnerability due to reduced physiological reserves, leading to impaired gait, balance, and muscle weakness. It also causes functional decline, which elevates the risk of falls, disability, hospitalization, and rapid progression to dependency. Early identification of frailty is crucial for enabling timely preventive interventions and improving health outcomes and quality of life among elderly individuals. To address this challenge, this study presents a machine learning-based frailty detection system that enables continuous and remote monitoring of gait characteristics in indoor environments. The proposed system is integrated with an Ultra-Wideband (UWB) indoor positioning system to provide precise localization. It employs a wearable UWB tag equipped with a tri-axial accelerometer for data collection. Data stream processing techniques are applied to perform real-time gait analysis and frailty detection from acceleration data patterns. Experimental results demonstrate that the proposed system is practical for real-world deployment. Among the evaluated models, the Random Forest model achieved the best overall predictive performance, with an overall classification accuracy of approximately 87.32% and an average false positive rate of 6.3%.

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1. INTRODUCTION

An aging society has become an increasingly common concern globally. According to the United Nations, several countries are experiencing growth in the number and proportion of older people in their population. The global older population, defined as individuals aged 65 and older, is projected to increase significantly from approximately 703 million in 2019 to an estimated 2.1 billion by 2050 [22]. Aging is becoming a major social problem in Thailand as well. According to the latest national statistical report, the proportion of older people in the population continues to increase, while the proportion of young people (those under 15 years of age) has declined significantly. Older people accounted for 20.17% of Thailand's total population in 2023. It is projected that the proportion of older population will increase to 31.37 percent by 2040, and the country is expected

to become a super-aged society within the next 15 years [5]. This demographic shift presents major challenges for economies, healthcare systems, and social structures. Societies must adjust to the changing needs of older people. In response to the challenges posed by an aging society, advanced technologies have emerged as important tools for improving the quality of life, promoting independence, and supporting efficient long-term care for older people.

Older people often experience a variety of medical issues stemming from the decline in health that accompanies aging. One of the significant problems is a decline in health and physical function, generally called Frailty syndrome. Frailty can be broadly defined as a clinical condition characterized by increased vulnerability due to reduced physiological reserves and function across multiple systems [23]. Frailty has multiple causes and contributors, either physical or

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psychological, or both. Older people with frailty are typically unable to engage in activities of daily living (ADLs). They usually face various health issues including unintentional weight loss, poor gait and balance, loss of muscle mass and strength, and cognitive impairment. Furthermore, older people with frailty are at higher risk of adverse health outcomes, such as falls, disability, and hospitalization. To effectively reduce, prevent, or even reverse decline associated with frailty, early identification of frailty in older people is crucial. Early identification of frailty enables medical staffs to implement timely preventive interventions that can improve physical function, enhance quality of life, and prevent further functional decline. Early monitoring of older people, particularly in indoor environments is important to prevent falls and injuries. This enables early diagnosis and targeted interventions such as personalized exercise programs and nutritional support, which can significantly reduce the risk of adverse outcomes, including hospitalization and disability.

To address the problem, particularly the need for early detection of frailty, we developed a machine learning-based frailty detection system that can remotely analyse gait characteristics and enables the timely detection of frailty among older people in indoor environments. The system is designed as a gait analysis tool that can continuously monitor gait characteristics, such as gait speed and step regularity, based on acceleration data patterns. In our system, an Ultra-Wideband (UWB) positioning system is used to enable highly precise and accurate indoor positioning and tracking of elderly individuals. A set of UWB anchors is installed above the area to create the location infrastructure. A UWB tag equipped with a tri-axial accelerometer must be securely attached to the older person using an elastic waist belt. The UWB tag continuously submits sensor measurements, consisting of acceleration and location data, to our frailty detection system for processing. Our system utilizes stream mining techniques for gait assessment. It executes a machine learning model for gait analysis over fast, high-volume streams of sensor measurements. Instead of storing sensor measurements on arrival, the data are processed dynamically and continuously without requiring persistent storage. By employing a data stream mining approach, low-latency frailty detection can be achieved.

This study makes four major contributions to the state of the art. First, it proposes a frailty detection method that enables real-time frailty detection through gait analysis. Second, the study presents an architecture for real-time frailty detection systems in indoor environments, providing a technical framework for developing practical frailty detection systems. Third, the study provides a comparative performance evaluation of machine learning models for frailty classification. Based on the experimental re-

sults, the Random Forest algorithm was selected to develop the final machine learning-based frailty detection model because it demonstrated superior classification performance. Fourth, the study evaluates the performance characteristics of the proposed frailty detection system. Under the specified testing environment, the system supported up to 1,000 concurrent users while maintaining an average response time of approximately 3 milliseconds and a communication reliability of at least 99%.

The rest of this paper is organized as follows. Section 2 reviews previous research on frailty detection systems. Section 3 introduces an architecture for real-time frailty detection systems. Section 4 presents our frailty detection approach in detail, including data collection, data preprocessing, and a frailty detection algorithm. Section 5 presents the implementation of a prototype for a real-time frailty detection system. Section 6 demonstrates the experimental evaluation in terms of frailty detection accuracy. Section 7 evaluates the system's real-time stream processing performance in terms of throughput and response time under increasing numbers of concurrent users. Finally, Section 8 presents conclusions.

2. RELATED WORK

Recent advances in ubiquitous computing have enabled the development of assistive technologies that support activities of daily living, reduce safety and health risks, and preserve physical function among older people [10,11,15,16]. Frailty detection has emerged as a critical research area in this context. Frailty is commonly defined as a clinical syndrome characterized by a decline in physiological reserves across multiple systems, resulting in increased vulnerability to stressors and a higher risk of adverse health outcomes [7]. Given the importance of early frailty detection, many studies have investigated a variety of approaches and techniques for frailty assessment [6].

Conventional mobility tests that assess muscle strength and postural balance in older people are among the earliest approaches to frailty detection. Millor *et al.* [12] proposed a system for identifying elderly individuals at risk of frailty using the sit-to-stand (SiSt) test. Multiple inertial sensors were attached to individuals' bodies to capture parameters, such as movement duration and body orientation. Building upon this work, Panhwarr *et al.* [13] introduced a frailty assessment method based on kinematic parameters extracted from SiSt movements performed during daily living activities (ADLs). Greene *et al.* [8] proposed a comprehensive frailty assessment platform that integrated data collected from three mobility tests: Timed Up and Go (TUG), quiet standing balance, and the Five Times Sit-to-Stand (FTSS) test. Sensor-derived features were used to train a Support Vector Machine (SVM) classifier for frailty classification. Experimental re-

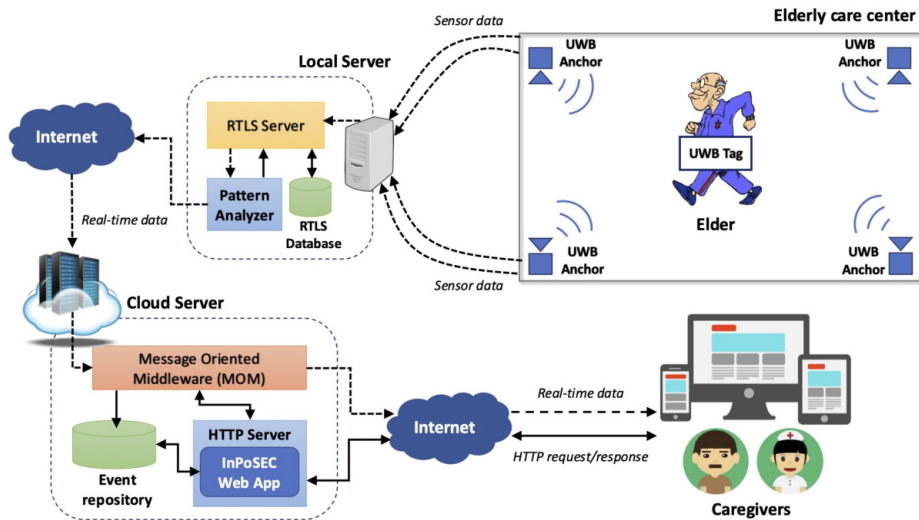


Fig.1: The system architecture for a frailty detection system based on Ultra-Wideband (UWB) positioning technology.

sults showed that combining raw data from multiple mobility tests improved frailty detection performance.

Caliskanelli *et al.* [2] approached frailty detection from a perspective distinct from earlier studies. Instead of collecting data during mobility tests, the study extracted data from detected joint and skeletal positions. A Kinect sensor was used to perform non-intrusive gait analysis for frailty assessment. Although no concrete result was reported, the authors suggested that non-intrusive sensing technologies could provide an efficient and practical solution for frailty detection. Charlon *et al.* [3] proposed a frailty monitoring system based on sensor-embedded shoe insoles. The smart insoles were capable of measuring body weight and automatically classifying physical activities, with the potential to integrate additional sensors for continuous monitoring of frailty-related factors including balance, weight changes, and gait impairment. Abbas and Jeannès [1] developed a machine-learning-based frailty detection system using wearable gait analysis. Accelerometers were placed on elderly participants at two body locations - waist and necklace - and Support Vector Machines (SVM) were trained using five gait-related features, including step rate and gait dynamism. The proposed system achieved an overall accuracy of approximately 88.5% for frailty classification.

The study by Tegou *et al.* [19] proposed an indoor monitoring system for frailty assessment. The system employed a low-cost Bluetooth-based indoor localization infrastructure to enable room-level mobility monitoring. Ten mobility-related features were extracted, including the number of room transitions and the proportion of fast and slow transitions. Five supervised machine learning models were evaluated, with the Random Forest (RF) model yielding the

best performance. The RF classifier achieved an accuracy of 82.33% in frailty classification. Kaur *et al.* [9] investigated the use of a logistic regression model to predict sarcopenia-related frailty. The proposed model analyzes demographic information, physical-related performance measures, and health-related variables to estimate the likelihood of sarcopenia frailty. Unlike many studies, this work utilizes non-sensor-derived data obtained from conventional assessments and clinical evaluations, making the approach more accessible and easier to implement in routine healthcare settings. Chou *et al.* [4] proposed a machine learning-based case definition for early frailty detection. The study utilized Electronic Medical Record data and trained four different supervised models. Among the evaluated models, the SVM achieved the best predictive performance, with an accuracy of 73.15%. However, the study has some limitations, particularly the use of an imbalanced dataset for evaluation.

The system presented in this paper aims to improve on the state of the art in several respects. It addresses the problem of frailty detection in indoor environments similar to [19]. It utilizes wearable sensors following approaches in [1,8,12,13] to capture data for extracting gait characteristics. To this end, stream-processing techniques are integrated with a machine-learning algorithm to enable frailty classification over continuous data streams. Furthermore, this work extends the studies of Abbas and Jeannès [1] and Chou *et al.* [4] by introducing a Random Forest-based frailty detection model as the final selected solution. Unlike prior approaches that require multiple sensors mounted at various body positions, the proposed system relies on a single wearable device attached at the waist. This design reduces the intrusiveness of the system, improves user comfort and

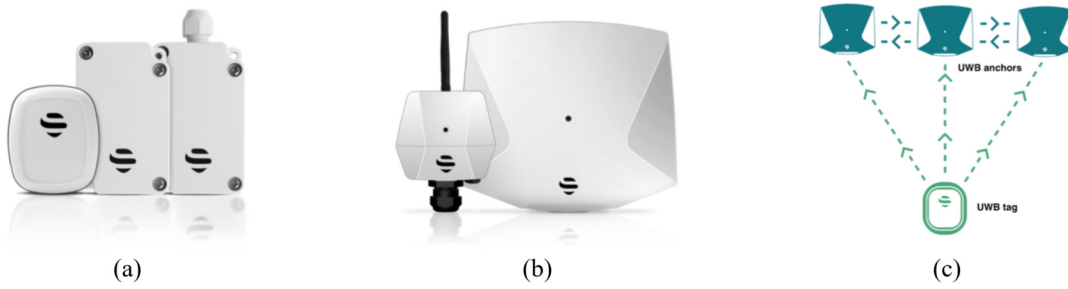


Fig.2: UWB sensing devices used in the architecture for indoor frailty detection systems: (a) UWB tags, (b) UWB anchors and (c) Communication between a UWB tag and a set of UWB anchors (SEWIO UWB RTLS Platform [17]).

engagement, and maintains high accuracy in frailty detection, as recommended by previous studies on monitoring systems for older people [20,21]. In addition, unlike many existing studies that focus solely on wearable sensor data, the proposed system integrates with an Ultra-Wideband (UWB) positioning system to provide precise real-time indoor localization. Integrating UWB positioning information with acceleration data enables context-aware frailty monitoring by combining gait characteristics with spatial movement patterns in indoor environments. This enables the system to analyze gait-related patterns and monitor mobility patterns and location-based behavioral changes that may indicate frailty.

3. SYSTEM ARCHITECTURE

To address frailty detection in indoor environments, we have specified an architecture for real-time indoor frailty detection systems. In this study, a frailty detection system is defined as a computer-based system that uses sensor data to monitor the physical activities of older people and assess frailty in real time. Such a system implements the architecture for real-time indoor frailty detection. The architecture allows us to describe the structure of the frailty detection system, its software components, and the interactions between components. The system architecture is presented in Fig.1.

We first present the hardware infrastructure on which the architecture relies. In this system, an indoor positioning system based on Ultra-Wideband (UWB) technology is employed as the underlying infrastructure for real-time localization. Two types of electronic sensing devices are utilized: signal transmitters, referred to as tags, and signal receivers, referred to as anchors. UWB anchors are stationary devices that are typically installed at predefined locations. They serve as reference points for the system by receiving signals transmitted by the tags. In contrast, UWB tags serve as mobile components attached to objects or individuals, such as older people, and can move freely within the designated tracking

area. The operation of the UWB indoor positioning system relies on communication between a tag and multiple anchors. During system operation, a UWB tag periodically emits UWB signals, which are captured by a set of anchors deployed within the predefined area of interest. The anchors then record the Time Difference of Arrival (TDoA) of the signals received from the tag. Finally, a backend server, known as the Real-Time Location Server (RTLS), uses this timing information to determine the precise location of the tag. Examples of UWB sensing devices used in our system architecture are illustrated in Fig.2.

We now describe the software components of the system architecture. In this architecture, a message-oriented middleware (MOM) plays a central role. It provides an infrastructure for transmitting sensor data streams between a local server at the elderly care center, a cloud-based processing server, and a client application. To ensure personal data protection during message transmission via the MOM, the MQTT protocol was secured using TLS/SSL encryption and authenticated communication mechanisms. Two different groups of users are involved: 1) older people who stay at an elderly care center and perform typical activities of daily living and 2) medical staff or caregivers who provide care and medical advice for older people. Note that older people are required to wear a UWB tag at all times. It is utilized as a data collection device for real-time tracking of indoor position, gait characteristics, and activities of older adults.

To monitor the gait characteristics of older people, a UWB tag transmits sensor measurements, including acceleration data, to a set of interconnected anchors by embedding the data in standard UWB communication packets. The anchors then record TDoA measurements and relay the UWB communication packets to a local server running the Real-Time Location Server (RTLS) software for location tracking. The RTLS server acts as a mediator, facilitating communication between UWB tags and software services running on the local server. It collects sensor data and transforms them into stream events specifically

Table 1: List of the classification features extracted and summarized from the raw acceleration data.

Feature	Description
Mean	Average acceleration values along the three axes (X, Y, and Z)
Min	The minimum acceleration within the window along the three axes (X, Y, and Z)
Max	The maximum acceleration within the window along the three axes (X, Y, and Z)
Standard deviation	The standard deviation in the acceleration values within the window along the three axes (X, Y, and Z)
Step length	The average distance measured between the point where one foot touches the ground and the point where the opposite foot touches the ground (meters). $\text{Step}_{\text{Len}} = \frac{\text{walking distance covered (m.)}}{\text{no. of steps detected}} \quad (1)$
Step frequency	The number of steps completed per second for a specific walking distance (steps/s). $\text{Step}_{\text{frq}} = \frac{\text{no. of steps detected}}{\text{duration of time spent walking (s.)}} \quad (2)$
Gait Speed	Time spent walking on a specified walking distance (m/s). $\text{Gait}_{\text{spd}} = \frac{\text{walking distance covered (m.)}}{\text{duration of time spent walking (s.)}} \quad (3)$
Root Mean Square Acceleration	The average change in amplitude of acceleration while walking on a specific distance (m/s²). $\text{RMS} = \frac{\sum_{i=1}^n \sqrt{a_x(i)^2 + a_y(i)^2 + a_z(i)^2}}{n} \quad (4)$
Step Regularity	The consistency in steps evaluated by comparing the landing times of the left and right legs for each pair of consecutive steps. [20] $\text{Step}_{\text{Reg}} = 1 - \frac{ T_{\text{STEP_R}}(i) - T_{\text{STEP_L}}(i) }{\max(T_{\text{STEP_R}}(i), T_{\text{STEP_L}}(i))} \quad (5)$ where $T_{\text{STEP_R}}$ and $T_{\text{STEP_L}}$ are the time duration of the right and left steps respectively

designed for gait analysis. After that, the stream events are forwarded to the Pattern Analyzer Service (PAS), responsible for performing real-time gait analysis. PAS is executed dynamically over stream events. If frailty is detected, a notification event is immediately created and sent to the client application via the MOM. Furthermore, medical staff can submit queries through web services to retrieve information about their older patients, such as gait parameters and location history, from the event repository.

4. FRAILTY DETECTION METHOD

4.1 Data collection

Our data collection process, along with the classification features extracted from acceleration data recorded during elderly physical activities, is de-

scribed as follows. These extracted features are used by our machine learning-based algorithm to develop a predictive model for detecting frailty in older people based on their gait patterns.

The data collection was conducted with 74 elderly participants aged between 61 and 82 years (mean age: 72 years) and 27 young staff members aged below 50 years (mean age: 41 years) from the senior club of the public health service center 56, Thap-Charoen, Bangkok. The participants were divided into three groups: 27 healthy young adults (YA), 42 healthy older adults (HOA), and 32 older adults with mobility problems (OAM). The OAM group comprises older people with physical frailty resulting from sarcopenia, characterized by slowness and reduced muscle mass, while retaining the ability to move independently. During our data collection experiment, each

participant wore a UWB tag attached to the waist using an elastic waist belt. They were then instructed to walk for approximately 5 minutes within an area equipped with UWB anchors. Throughout the walking trial, raw data were collected from the embedded accelerometer at a sampling frequency of 10 Hz using a lightweight application service running on a local server, PAS. The collected acceleration data were subsequently processed to extract statistical features that characterize gait patterns for use in machine learning model development. Table 1 summarizes the features extracted from the raw data. Note that the total number of extracted features was 17, of which the first 12 were used for activity classification, while the remaining features were gait-related features used for frailty detection. The activity classification features were extracted using a time-based window of 3 sec, whereas the gait-related features were computed using a distance-based window of 10 meters.

4.2 Data preprocessing

Raw acceleration data collected from wearable sensors are inherently noisy due to hardware limitations, electrical interference, sensor drift, and motion-induced artifacts. Without appropriate preprocessing, these distortions may propagate to the feature extraction and learning stages, leading to reduced classification performance. To mitigate these effects, a two-phase data preprocessing procedure was employed.

In the first phase, a mean average filter was applied to smooth the three-axis acceleration data to reduce high-frequency noise while preserving the overall motion trend. The filter operates by replacing each acceleration sample with the average of its neighboring samples within a sliding window, thereby reducing short-term fluctuations caused by sensor noise and minor motion artifacts. In the second phase, the data are further processed using a Moving Average Threshold (MAT) technique for step detection. In this context, a moving average is computed for each sliding window. The resulting moving average value is then used as an adaptive threshold for step detection. A step event is detected when the acceleration signal exceeds this threshold. The MAT can be described as follows:

$$MA(n) = \frac{1}{W} \sum_{k=0}^{w-1} x(n-k) \quad (6)$$

In this formulation, $MA(n)$ denotes the moving average value at time index n , while $x(n)$ represents the input acceleration value at time index n . The parameter W represents the moving average window size, defined as the number of consecutive acceleration samples included in the averaging process. In this study, W is set to 20 by default.

4.3 Frailty detection algorithm

We now explain our real-time frailty detection algorithm. Our idea is grounded in a preventive medicine approach that emphasizes helping older adults mitigate potential health problems by promoting healthy behaviors and early disease screening, rather than focusing on treatment after conditions have already developed. Previous studies on frailty have identified sarcopenia as an important indicator of frailty because it can impair mobility, balance, and physical independence. Frailty is basically a state of reduced physiological reserve, and muscle strength is one of the body's key reserves; when muscles deteriorate, older adults become more vulnerable to falls, slower recovery, hospitalization, and reduced quality of life. Therefore, this study focuses on frailty-related health outcomes associated with sarcopenia.

Gait analysis is a powerful way to identify sarcopenia, because muscle weakness alters how older adults walk even before severe symptoms appear. Sarcopenic individuals typically show slower gait speed, shorter step length, longer double-support time, reduced push-off power, and decreased variability control. Early detection of such gait abnormalities using wearable sensors provides an objective approach for screening for sarcopenia and frailty. Early identification is clinically important because targeted interventions, such as resistance training, protein supplementation, and balance exercises, can significantly improve muscle function and slow the progression of frailty.

Our frailty detection algorithm builds on this concept by analyzing gait patterns using acceleration data collected while older adults walk. It employs data stream processing techniques that enable machine learning models to operate in real time. The approach leverages a stream processing engine with stateful computation components to support a continuous stream data pipeline. Through this stream processing framework, the algorithm can react to incoming acceleration data events as they occur, achieving low-latency responses. The pseudocode of our proposed real-time frailty detection algorithm is presented in Fig. 3.

As illustrated in Fig. 3 our real-time frailty detection algorithm can be divided into three main phases, including the initialization phase, the data preparation phase - where gait-related features used for frailty classification are extracted - and the inference phase - where the trained frailty detection model applies the previously learned knowledge to make real-time predictions on new, unseen acceleration data. In the first phase, the key components for frailty detection - namely, the tumbling distance window ($dWin$) and the machine learning-based frailty detection model ($FDmodel$) - are initialized. The purpose of this phase is to prepare these components for use in subsequent phases. Specifically, the model

```

1: GLOBAL FDmodel = null;
2: GLOBAL stepTotal = 0;
3: /*The entry point where the algo execution begins*/
4: function INIT( )
5:   dWin = new distanceWindow(distanceThres: 10);
6:   dWin.set(callbackFunc);
7:   trainingData = loadDataset();
8:   FDmodel = trainFrailtyDetectionModel(trainingData);
9: end function
10: /*The frailtyDetection() is called when an event is
11: added to the inbound queue */
12: function FRAILTYDETECTION(input_event)
13:   currentAct = getCurrentActivity(input_event);
14:   if currentAct is "walking" then
15:     movingAverageFilter(input_event);
16:     stepCnt = detectStep(input_event);
17:     if stepCnt is greater than 0 then
18:       stepTotal = stepTotal + stepCnt;
19:     end if
20:     /* put an event into the distance window */
21:     dWin.add(input_event);
22:   end if
23: end function
24: /* The callback() is triggered once the threshold
25: - 10m distance - is reached. */
26: function CALLBACKFUNC(event_list)
27:   itm_event = computeGaitFeat(event_list, stepTotal);
28:   [class_id, class_name] = FDmodel.detect(itm_event);
29:   if class_id is "OAM" then
30:     sendNotificationMessage();
31:     stepTotal = 0;
32:   end if
33: end function

```

Fig.3: Real-Time Frailty Detection Algorithm.

is trained iteratively on the training dataset, allowing it to adjust its parameters to recognize acceleration patterns accurately.

In the second phase, input stream events, each consisting of a set of statistical features extracted from raw acceleration data, are collected. The input stream events are then forwarded to the frailty detection function (*frailtyDetection*) through the inbound queue. These events are first analyzed to determine whether the current physical activity of the older person is walking. Next, data preprocessing is performed on the acceleration data using the Moving Average Threshold (MAT) method (*movingAverageFilter*). After that, the number of steps is determined based on the adaptive moving average threshold. Using the number of steps together with time information, statistical data about gait characteristics can be calculated. Next, the tumbling distance window (*dWin*) is used to determine whether the accumulated walking distance is sufficient for feature extraction and gait assessment. The distance threshold we used in this calculation is 10 meters. This distance is commonly used to assess the walking speed of older people in the 10-Meter Walk Test (10MWT) [14].

Once the tumbling distance window generates an output, indicating that the older person has covered 10 meters, gait features are calculated to form a feature vector, including step length, step frequency, gait speed, root mean square (RMS) acceleration, and

step regularity. Then, a machine-learning based classification model is utilized. The model takes the feature vector derived from the previous step as its input. It then performs classification to obtain a classification result. Finally, if frailty is detected, a notification message is generated and sent to the client application via a message topic within the MOM. The details of our implementation will be discussed later in the prototype implementation section.

5. PROTOTYPE IMPLEMENTATION

The web-based client application, InPoSEC, is one of the key components of the proposed real-time frailty detection system. It provides a web-based user interface that enables medical staff and caregivers to remotely monitor frailty in older people, track their indoor locations in real time, and access physical activity statistics. One of the primary requirements of the system is the ability to operate on both general-purpose computers and a wide range of mobile devices via the Internet. This requirement is addressed through a responsive user interface that adapts to various screen sizes.

Furthermore, because each caregiver is responsible for monitoring multiple older people simultaneously, the collected information must be presented in a clear and efficient manner. This requirement is addressed using Asynchronous JavaScript and XML (AJAX) in combination with RESTful web services and Web-Socket technology. In addition, the client application provides an activity log feature that stores detailed physical activity data performed by elderly users in a secure database. These data, together with the measured gait characteristics, can be used for further assessment of frailty. The main features of the client application are summarized as follows:

- Frailty monitoring and detection: continuously monitors physical activities and detects signs of frailty while older people are walking in real time. An instant notification message is generated and sent to medical staff when frailty is detected.
- Indoor location tracking: precisely determines the current indoor location of older people and updates their locations on a map in real time.
- Activity log: records and displays historical data on the physical activities performed by older people, such as walking, standing, sitting and lying.
- Personal information: provides access to older people's health, medication, and contact information to support medical staff in providing appropriate care and treatment for frailty.

Furthermore, the web-based client application provides additional features, including caregiver alerts, geo-fencing, and support for monitoring multiple elderly patients simultaneously. Example screenshots of the web-based client application (InPoSEC) are

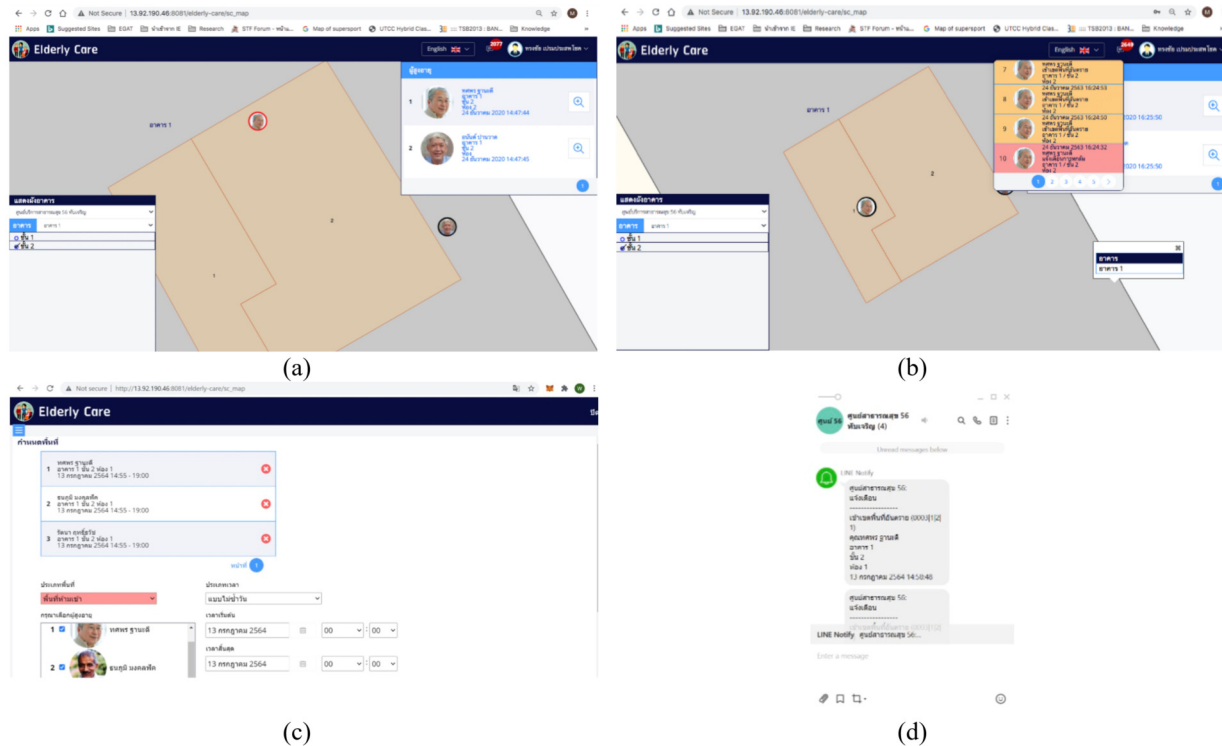


Fig.4: Example screenshots of the web-based client application for frailty detection: (a) Indoor location tracking function, (b) Frailty monitoring and detection function, (c) Geo-fencing function, (d) Caregiver alert function.

shown in Figure 4. Figure 4(a) presents a screenshot of the indoor location tracking function allows caregivers to remotely monitor the locations of older people in real time. Figure 4(b) shows a screenshot of the frailty detection function, where medical staff or caregivers are notified and can query detailed information about the older person's condition when frailty is detected. Figure 4(c) illustrates a screenshot of the geo-fencing function, which enables caregivers to receive notifications when an elderly individual enters a predefined dangerous area. Finally, Figure 4(d) displays a screenshot of the notifications received by caregivers via LINE messages.

6. EVALUATION OF MACHINE-LEARNING BASED FRAILTY DETECTION MODELS

The primary objective of this evaluation is to assess the classification accuracy of the proposed machine learning-based models for real-time frailty identification and to compare their performance. The classification models were developed using the WEKA machine learning toolkit, an open-source machine learning framework implemented in Java. WEKA was selected because it enables the development of a self-contained classification model that can be deployed and executed. In addition, WEKA facilitates systematic experimentation with multiple machine learning algorithms using statistical features ex-

tracted from acceleration data as the training dataset, enabling the selection of a model that meets the system requirements.

In our experimental evaluation, five algorithms - the Decision Tree (DT), Support Vector Machine (SVM), Feedforward Neural Network (Multi-layer Perceptron, MLP), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) - were selected to develop the proposed machine learning models. These algorithms were chosen because they represent fundamentally different learning paradigms, enabling a comprehensive and balanced performance evaluation. Each algorithm offers distinct advantages in interpretability, generalization capability, and non-linear pattern modeling, which are important for handling complex sensor-based data. To improve model performance and enhance each algorithm for the frailty classification task, hyperparameter tuning was performed for all proposed machine learning models. This tuning process aimed to identify some appropriate parameter configurations that optimize predictive performance while maintaining a fair and stable comparison among models. The hyperparameters used in this experimental evaluation are described as follows:

The decision tree model was implemented using the C4.5 algorithm (J48) with a confidence factor of 0.25 for pruning, a minimum of two instances per leaf, and reduced-error pruning disabled. The SVM model



Fig.5: Data collection and experimental evaluation at the public health service center 56, Thap-Charoen, Bangkok.

was implemented using C-Support Vector Classification (C-SVC) with a Radial Basis Function (RBF) kernel, a gamma value of 0.1, and a complexity parameter (C) of 10. The MLP model was configured with two hidden layers containing 12 and 6 nodes, respectively, with the layer sizes determined based on the number of input attributes. The learning rate was set to 0.3 together with a momentum of 0.2. The Random Forest model was configured with 100 decision trees to improve classification robustness and reduce overfitting. The model employed automatic random feature selection at each split with a minimum leaf instance weight of 1.0. The XGBoost model was configured with 500 boosting trees. The learning rate was set to 0.03, and the maximum tree depth was limited to 3 to improve generalization performance.

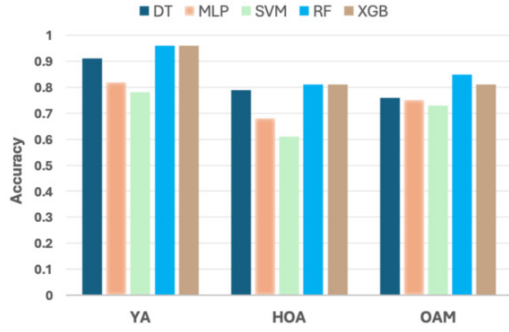
For the experimental setup, as described earlier, the participants were categorized into three groups: young adults (YA), healthy older adults (HOA), and older adults with mobility problems (OAM), the latter representing physically frail elderly individuals primarily affected by sarcopenia. Four Ultra-Wideband (UWB) anchors were installed in the main building of the public health service center 56, our research partner, to establish an indoor location tracking infrastructure. During the experiment, each participant wore a UWB tag securely attached to the waist using an elastic belt while walking. All participants walked within the area covered by the installed UWB anchors, with each walking session lasting five minutes. The UWB tag captured raw acceleration data and transmitted it to a local server for processing. Upon reception, the raw sensor data were dynamically transformed into instances (feature vectors) by extracting gait-related features and assigning corresponding class labels. These instances were then used as a training dataset to build the classification model, which was subsequently deployed as a microservice for frailty detection. The experiment setup at the public health service center 56 is illustrated in Figure 5.

Our machine learning-based frailty detection model was evaluated for its classification accuracy in identifying participant groups based on gait char-

acteristics (extracted gait-related features). The dataset used in this experiment consisted of 1,420 instances, including 456, 476, and 488 instances from the YA, HOA, and OAM groups, respectively. Model performance was assessed using 10-fold cross-validation, which was selected to ensure a reliable and unbiased estimation of generalization performance while making efficient use of the available data. The performance of the proposed frailty classification model is illustrated in Figure 6.

As illustrated in Figure 6(a), among the five evaluated algorithms, the Random Forest (RF) model achieved the highest average accuracy for frailty classification, with an overall accuracy of 87.32%. When analyzed by participant group, the model achieved its highest classification accuracy for the YA group, at 96.05%. This was followed by the OAM and HOA groups, which achieved accuracies of 85.09% and 81.35%, respectively. However, the confusion matrices presented in Figures 6(b)–6(f) indicate considerable misclassification between the healthy older adult (HOA) and older adults with mobility problems (OAM) groups across all five models. This may be attributed to the similarity in gait patterns among elderly individuals. Among the five models, the Random Forest model demonstrates the best classification performance, with a misclassification rate of less than 10%. In contrast, the other four models exhibit misclassification rates exceeding 10%. In particular, the MLP and SVM models exhibited relatively high error rates, misclassifying more than 20% of OAM instances as HOA, at 20.38% and 21.64%, respectively.

Moreover, when comparing the five proposed frailty detection models across multiple evaluation metrics, the Random Forest model achieved the best overall classification performance, obtaining the highest Recall and F1-score, as shown in Figure 7. These results indicate that the model was highly effective in correctly identifying positive frailty cases while maintaining a good balance between sensitivity and precision. The Random Forest model also produced the lowest false positive rate (6.3%), demonstrating superior robustness and reliability for frailty classification. The other tree-based models, including XGBoost



(a) Accuracy comparison

		Predicted Class		
		YA	HOA	OAM
Actual Class	YA	91.45%	3.51%	5.04%
	HOA	6.15%	78.89%	14.96%
	OAM	8.61%	15.97%	75.42%

(b) DT model

		Predicted Class		
		YA	HOA	OAM
Actual Class	YA	81.14%	4.17%	14.69%
	HOA	7.79%	67.62%	24.59%
	OAM	4.62%	20.38%	75.00%

(c) MLP model

		Predicted Class		
		YA	HOA	OAM
Actual Class	YA	78.07%	9.21%	12.72%
	HOA	5.74%	61.27%	32.99%
	OAM	5.04%	21.64%	73.32%

(d) SVM model

		Predicted Class		
		YA	HOA	OAM
Actual Class	YA	96.05%	0.22%	3.73%
	HOA	2.87%	81.35%	15.78%
	OAM	6.51%	8.40%	85.09%

(e) Random Forest model

		Predicted Class		
		YA	HOA	OAM
Actual Class	YA	95.61%	0.66%	3.73%
	HOA	3.07%	81.56%	15.37%
	OAM	6.73%	12.39%	80.88%

(f) XGBoost model

Fig. 6: Performance of the proposed frailty detection models (a) Comparison of the classification accuracies among frailty detection models, (b)-(f) The confusion matrix for the decision tree (DT), the Support Vector Machine (SVM), the feedforward neural network (MLP), the Random Forest (RF) and the XGBoost (XGB) models.

and Decision Tree, also achieved relatively strong performance compared to MLP and SVM models. This may be attributed to the low-dimensional gait-related features used in this study, which likely exhibit threshold-like and moderately nonlinear relationships that are naturally well suited to tree-based learning approaches.

Furthermore, the Receiver Operating Characteristic (ROC) curves presented in Figure 8 provide further evidence of the superior classification performance of the Random Forest (RF) model compared with the other proposed models. Based on the ROC, the RF model showed the highest classification performance, with an Area Under the ROC Curve (AUC) of 0.95, outperforming the DT (AUC = 0.85), MLP (AUC = 0.86), SVM (AUC = 0.81), and XGB (AUC = 0.93) models. In addition, the AUC value exceeding 0.9 indicates that the Random Forest model demonstrates excellent discriminative performance in

detecting frailty based on gait characteristics.

Following comparative experimental evaluation, the Random Forest algorithm was selected to construct the final frailty detection model. The results suggest that the Random Forest model provided the most balanced and reliable performance for real-time frailty detection, achieving high sensitivity and stable classification performance while minimizing false positives. Another important observation is that tree-based ensemble models, particularly the Random Forest and XGBoost, consistently outperformed individual learning approaches such as DT, SVM, and MLP across all evaluation metrics. This may be because ensemble learning techniques combine predictions from multiple trees, enabling them to capture nonlinear relationships and threshold-like patterns commonly found in gait-related features in this study.

		Evaluation metrics			
		Accuracy	Recall	F1-score	FP rate
ML Model	DT	81.76%	0.818	0.816	0.092
	SVM	72.18%	0.722	0.724	0.141
	MLP	78.59%	0.786	0.785	0.107
	RF	87.32%	0.873	0.873	0.063
	XGB	85.98%	0.860	0.859	0.070

Fig.7: Performance comparison of the proposed frailty detection models across evaluation metrics.

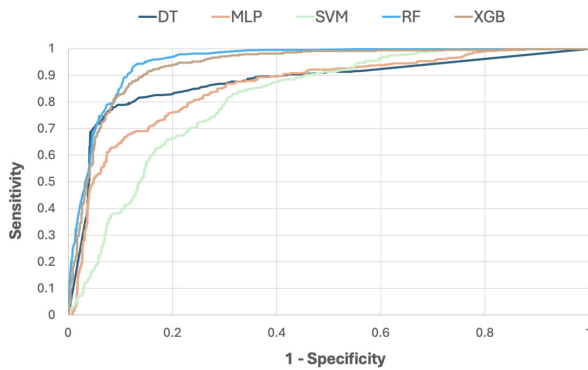


Fig.8: The ROC curves of the proposed detection models.

7. EVALUATION OF REAL-TIME STREAM PROCESSING PERFORMANCE

This section discusses the evaluation of the system's real-time stream processing performance. We primarily focused on measuring the message transmission and reception between the Message-Oriented Middleware (MOM), which serves as the central communication component of the proposed system architecture. The performance evaluation was conducted using JMeter, an open-source software tool widely used for load and performance testing. The details of the testing environment and configuration are described as follows.

The performance testing was conducted using JMeter version 5.4.1. JMeter was configured to send and receive messages with the MOM and to generate multiple threads to simulate increasing numbers of concurrent users. JMeter was run on a personal computer equipped with an Intel Core i5 3.2 GHz processor (4 cores, 4 threads, 6 MB cache), 16 GB of RAM, 1 TB of HDD storage. For the server-side environment, the MOM software utilized was Apache ActiveMQ version 5.15.10 running on Java Virtual Machine (JVM) version 8. The server machine was configured with 4 vCPUs, 14 GiB of RAM, 30 GiB of SSD storage, and ran Ubuntu 18.04.5 as its operating system.

In the experiment, the Publish/Subscribe model

was adopted as the communication model, with a message topic serving as the communication channel for data exchange. The messages used during testing were actual data samples collected at the public health service center 56. Each message had a size of 610 bytes and was transmitted as a TextMessage. The messages were periodically transmitted every 3 seconds. A single producer thread, representing one simulated user, was configured to send 1,000 messages to the MOM running on the server machine. For each testing round, the number of simulated users was increased by 200, from 200 to 2,000 users. Furthermore, all producer threads were configured to start simultaneously without any startup delay. The performance evaluation results of the proposed system are illustrated in Figure 9.

As displayed in Figure 9(a), the performance evaluation began with 200 concurrent users. Under this configuration, the system transmitted 200,000 messages and successfully received all of them. Subsequently, the number of users was increased by 200 per testing round. The experimental results showed a consistent trend, with the system successfully handling all transmitted and received messages without errors. However, when the number of concurrent users reached 1,000 users, a total of 1,000,000 messages were submitted for processing. Under this condition, the system successfully delivered and received 999,000 messages, resulting in a communication error rate of about 0.1%. This indicates that the system reached its maximum throughput at 1,000 concurrent users, as shown in Figure 9(b). Furthermore, when the number of concurrent users increased beyond 1,000 to 1,200, 1,400, and 2,000, the error rate increased progressively. The observed error rates were approximately 16%, 28%, and 50% of the total submitted messages, respectively. These communication failures are consistent with the same limitation observed in the 1,000-user scenario, where the system had already reached its maximum throughput capacity and could no longer efficiently handle additional processing load. As shown in Figures 9(c) and 9(d), at 1,000 concurrent users, the system could process incoming messages at an approximate throughput of 332 messages per second. The average system re-

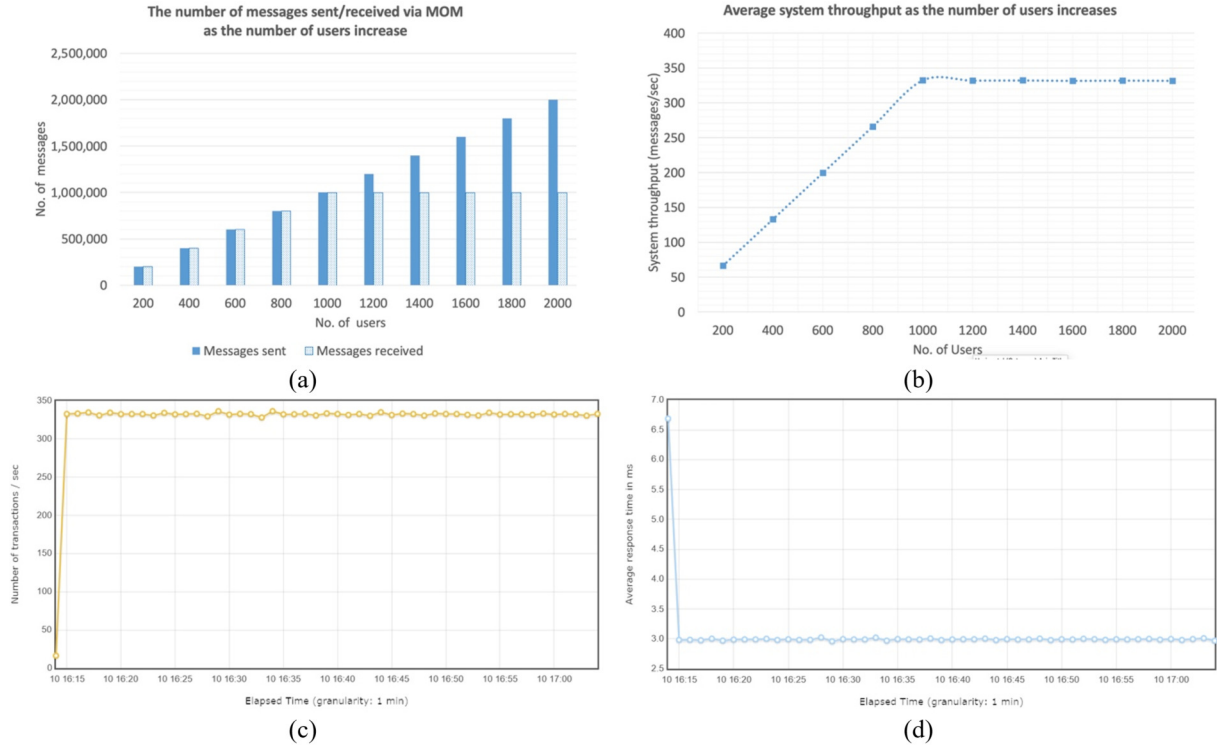


Fig.9: Evaluation results of the system's real-time stream processing: (a) The number of messages sent/received as the number of users increases, (b) System throughput as the number of users increases, (c) The number of transactions (messages) processed per second (1,000 users), (d) The average response time of the system (1,000 users).

sponse time was about 3 milliseconds, while the error rate remained very low at 0.1%.

8. CONCLUSION

In this paper, we propose an innovative frailty detection system that dynamically analyzes gait characteristics and detects frailty in older people in real time. We present the system architecture for real-time frailty detection, which serves as a technical blueprint for developing practical monitoring systems for elderly care. The technical aspects of constructing an indoor positioning infrastructure for elderly care are also described. To explain the operation of the proposed system, particularly the construction of the machine learning-based classification model for frailty detection, we describe the data collection process, the classification features extracted from acceleration data, the data preprocessing procedure, and the algorithm for real-time frailty detection. These features are then used as inputs to selected machine learning algorithms to develop classification models for accurately identifying frailty in older people. To evaluate the proposed frailty detection models, five machine learning-based algorithms are employed. Experimental results demonstrate that the proposed system can be effectively deployed in real-world environments, achieving an average system response time of approximately 3 milliseconds while maintaining a

communication reliability rate of at least 99%. Furthermore, the comparative performance analysis revealed that the Random Forest model achieved the best overall classification performance, with an overall accuracy of 87.32% and an average false positive rate of 6.3%. Based on these results, the Random Forest algorithm was selected to construct the final frailty classification model for the proposed real-time frailty detection system.

For future work, the proposed system will further integrate Ultra-Wideband (UWB) indoor positioning information to enhance frailty assessment by incorporating spatial and mobility-related information. Specifically, positioning information obtained from the UWB infrastructure will be integrated with acceleration data to enable more comprehensive analysis of gait patterns, mobility behaviors, and location-based behavioral changes in indoor environments. By integrating spatial movement information with sensor measurements, the system is expected to provide more comprehensive and context-aware frailty detection, thereby improving the accuracy and reliability of real-time elderly monitoring applications.

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AI USAGE STATEMENT

During the preparation of this manuscript, the authors used ChatGPT and Gemini to assist with language refinement, grammar checking, and improving sentence conciseness. Following the use of these tools, the authors carefully reviewed and edited the content and take full responsibility for the content of this publication.

AUTHOR CONTRIBUTIONS

Conceptualization, W.S., M.T., and I.K.; methodology, W.S.; formal analysis, W.S.; investigation, W.S.; writing—original draft preparation, W.S.; writing—review and editing, W.S., M.T., and I.K. All authors have read and agreed to the published version of the manuscript.

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