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INDOOR ACTIVITY RECOGNITION AND DEMENTIA RISK DETECTION USING Wi-Fi RECEIVED SIGNAL STRENGTH INDICATOR (RSSI) AND NAÏVE BAYES CLASSIFICATION

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ABSTRACT

Increasing life expectancy has resulted in a growing elderly population, making neurodegenerative conditions such as dementia a major global health issue. One of the main behavioral symptoms of dementia is wandering, which is characterized by repetitive and purposeless movement. Activity Recognition (AR) technologies, particularly those based on Wireless Sensor Networks (WSN), have gained attention for monitoring human behavior. Among these, Wi-Fi-based tracking using the Received Signal Strength Indicator (RSSI) offers a promising method for indoor activity monitoring and localization. This study aims to monitor the daily routines of elderly individuals, classify their current activity patterns by comparing them with previously recorded behaviors, and track their locations using Wi-Fi RSSI. A Naïve Bayes algorithm is proposed for activity classification and location tracking, while a time-based behavior graph is used to detect potential wandering behavior, aiding in early dementia risk assessment. The research utilizes primary data, which were collected directly through experiments in a controlled indoor environment. The data source comprises RSSI signals obtained from elderly participants. A purposive sampling method was employed to select participants aged 60 years and above, who were physically capable of performing the required tasks. A total of 4150 RSSI data samples were collected and analyzed. The proposed Naïve Bayes model achieved a classification accuracy of 64.60% using cross-validation, with a minimum average localization error of 0.7 meters, demonstrating the potential of this approach for early detection of dementia-related wandering behavior.

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1. INTRODUCTION

The rising life expectancy has resulted in a larger senior population, rendering neurodegenerative diseases such as dementia a major worldwide health issue. Dementia is a condition marked by cognitive deterioration, impacting memory, reasoning, and everyday tasks [1]. One of the primary symptoms of dementia is wandering, a repetitive and aimless movement pattern that can pose safety risks for individuals with dementia [2]. Early detection of wandering behavior is crucial for providing timely intervention and improving patient care.

In recent years, the intersection of machine learning, Internet of Medical Things (IoMT), and cloud computing has significantly advanced the field of healthcare diagnostics and monitoring. Technologies such as Convolutional Neural Networks (CNNs) have demonstrated remarkable success in medical imaging and biomedical signal analysis, enabling more accurate and earlier disease detection [3]. Systems like Blockchain-Based Heart Disease Monitoring using BS-THA and OA-CNN [4], as well as frameworks for secured data transfer in cloud environments employing KPCC and BiO-ELSTM models [5], highlight the growing integration of Artificial Intelligence (AI) with secure, scalable medical data management [6]. Additionally, Machine Learning techniques for biomedical signal processing are reshaping how physiological data is interpreted for clinical purposes.

Activity Recognition (AR) technology, particularly using Wireless Sensor Networks (WSN), has gained attention for monitoring human behavior in real-time. Research that utilizes theoretical and practical approaches to solve problems related to time sequences, such as human-computer interaction, is one of the studies on Human Activity Recognition (HAR) [7], [8], and besides that, smart homes [9], [10], and health monitoring [11], [12]. A commonly used object position tracking system is the Global Positioning System (GPS). In certain locations or outdoors, GPS can provide precise positioning, but for indoor use, it does not work well. That is the basis for tracking the location of objects using radio networks. WiFi RSSI-based indoor object position tracking is one of the standard approaches for indoor object positioning [13], [14], [15].

One of the promising techniques in AR is Wi-Fi-based tracking using Received Signal Strength Indicator (RSSI) [16], [17]. Unlike wearable sensor-based systems, Wi-Fi-based methods offer a more practical and non-intrusive solution for continuous monitoring [18]. A radar system utilizing received signal strength was proposed for indoor localization for the first time in 2000 [19]. By utilizing Wi-Fi, it can track the location of the object, which is represented in (x, y) coordinates. This study uses Wi-Fi-RSSI to determine the position of objects using two phases: training and positioning, using fingerprint positioning technology. When measuring the Wi-Fi RSSI, the database training was determined at the coordinates specified by the research center. Based on the need for knowledge of the training data, the fingerprint algorithm was classified as a suitable algorithm. The training data was calculated using a machine learning approach, the Naïve Bayes algorithm. Naïve Bayes is a simple and efficient classification for estimating location [20], [21].

A Bayes classifier is one of the statistical classifiers, where this classifier can predict the probability of class membership of a tuple of data, namely a data structure that stores several values in a certain order that will enter a certain class, according to probability calculations. A Bayes classifier is based on Bayes' theorem, discovered by Thomas Bayes in the 18th century. In a comparative study of classification algorithms, a simple Bayesian or, commonly known as the Naïve Bayes classifier, has been found. Naïve Bayes classifier shows high accuracy and speed when applied to large databases [22]. This method is often used in solving problems in the field of machine learning because this method is known to have a high level of accuracy with simple calculations [23]. In this study, we conducted a Naïve Bayes experiment to classify the location of unknown objects based on Wi-Fi RSSI. In most cases, Naïve Bayes can achieve good performance and is easy to implement. Naïve Bayes is a classification method in the probability framework [24].

The core idea is to obtain the minimum conditional risk of each sample as a class label, also known as posterior probability. The posterior probability of the online fingerprints located in each state space is calculated using Bayes' theorem; then, the state space with the maximum posterior probability is selected. As the simplest form of Bayesian network classifier, Naïve Bayes naively assumes that all features are independent of each other [25]. In the case of indoor position problems, class l nodes represent locations, and RSSI feature nodes correspond to the signal strength received from each AP. The results of the analysis by Naïve Bayes show that this algorithm is suitable for estimating the exact location of an object according to the Wi-Fi RSSI, and the movement patterns of a person in an indoor environment can be known, so that it can detect irregular activities related to dementia. Specifically, the research objective to be achieved is to be capable of observing the everyday actions of the elderly and subsequently categorize their current activity trends by contrasting them with previously saved patterns to identify early signs of dementia in the elderly, such as wandering, which can indicate early dementia. The novelty of this research lies in the integration of Naïve Bayes-based indoor positioning with behavioral pattern recognition for early dementia detection. Unlike previous studies that focused solely on positioning or activity classification, this work combines location estimation with time-series pattern matching to detect wandering behavior, a critical early symptom of dementia. Moreover, the system is designed to function using primary data collected from real elderly participants in a simulated indoor environment, with 4150 RSSI samples collected.

2. RESEARCH METHODS

The research methodology to be implemented consists of multiple phases or steps. In general, the stages of methodology and system design are divided into 5 main stages. The steps are shown as follows in Fig. 1.

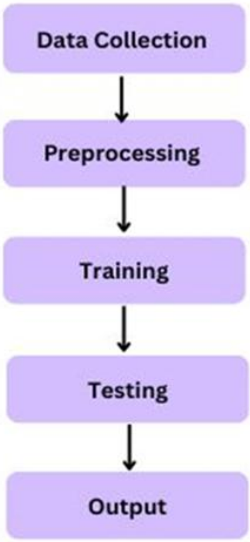


Figure 1. Flowchart for the Full Process

2.1 System Architecture

The research methodology includes several key steps to implement Activity Recognition (AR) and object positioning, specifically for elderly individuals. The process consists of the following stages:

2.1.1 Preparation of the Research Location

In this study, measurements were taken in the entire area used as the research location, namely, a house. The measurement results were obtained as much as 24×14 with the parts of the room shown in Fig. 2 the corresponding to the actual distance.

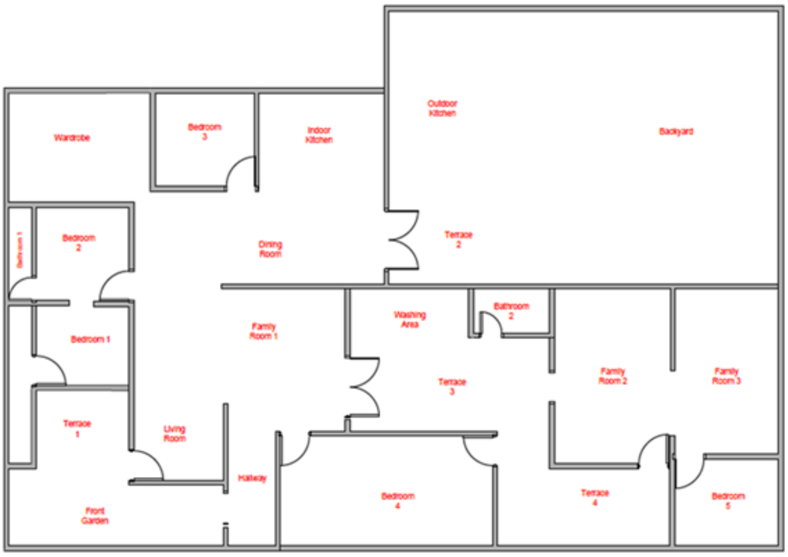


Figure 2. Research Location's Plan

To systematically capture movement data throughout the indoor environment, the entire research area was segmented into a 24×14 coordinate grid, with each point spaced 2 meters apart along both the x and y axes. This grid-based mapping corresponds to the actual spatial layout of the house and encompasses all functional rooms. It serves as the foundational structure for both the training and positioning phases of the indoor localization system

2.1.2 RSSI-Based Positioning Method

There are 2 stages in determining the position of an object, namely, the initial stage of measuring training data. At the training stage, Wi-Fi-based RSSI measurements are carried out by collecting RSSI at several predetermined coordinate points, namely, each point with a distance of 2×2 meters shown in Fig. 3, with a total of 83 coordinate points. Wi-Fi RSSI retrieval uses a laptop equipped with Net Surveyor software to record the Wi-Fi signal strength, given in Fig. 4. At each coordinate point, a Wi-Fi-based RSSI recording is carried out for 2 minutes. Then, the visualization to analyze the radio signal strength map Wi-Fi RSSI Evaluation uses Altair AI Studio 2025, and the second stage is the positioning stage.

Figure 3. Coordinate Points

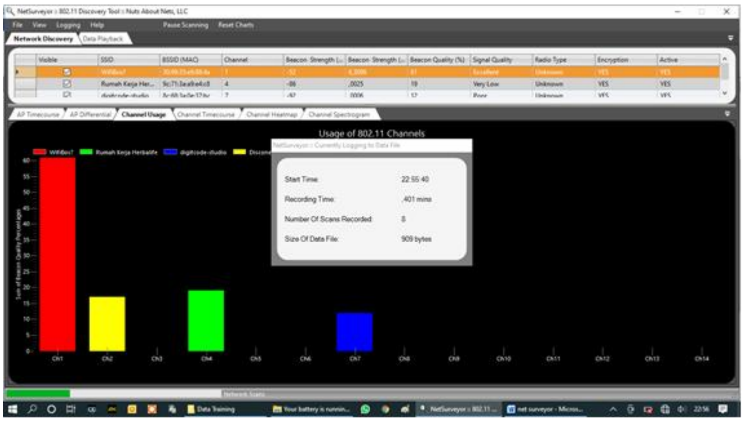
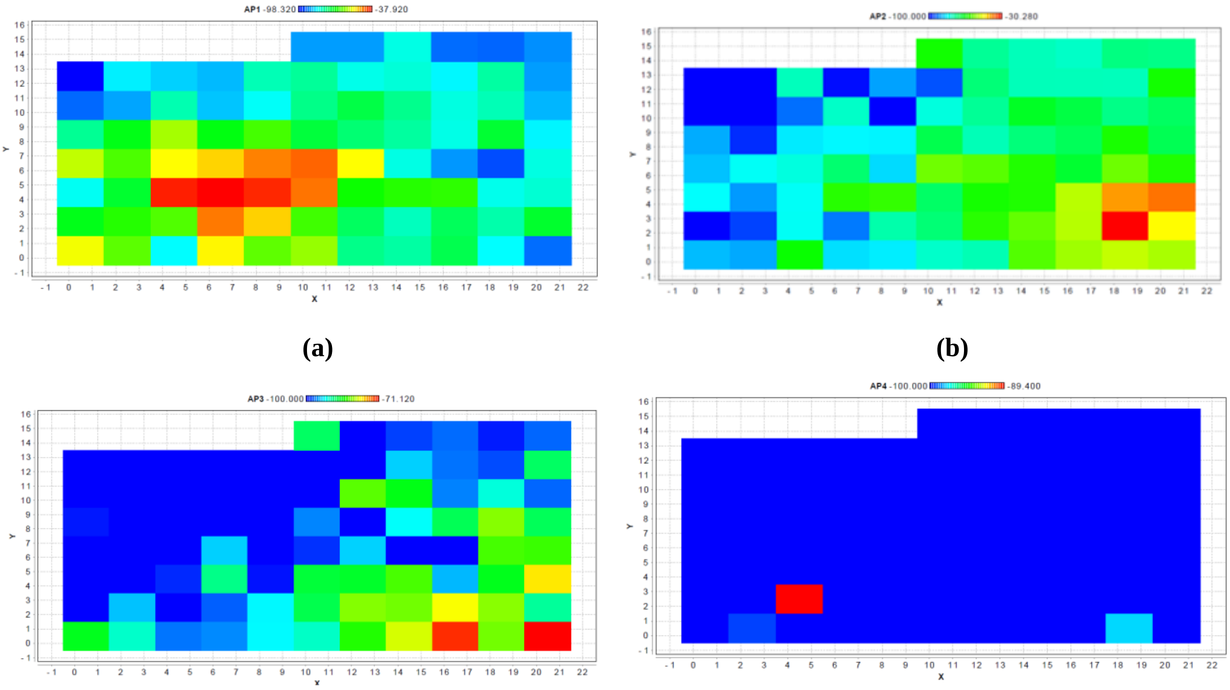


Figure 4. Net Surveyor Software for Measuring RSSI Values that Fluctuate Over Time for Multiple Wi-Fi Networks

The signal strength received at a coordinate point can be visualized to display a summary diagram showing the received signal strength. The purpose of signal strength visualization is to see the distribution of signal strength recorded at the research location. There are 4 Access Points (AP) recorded by Net Surveyor at the research location. Signal strength visualization is displayed in various colors, from the strongest in red and the weakest in blue. The results of signal strength training data measurements collected as many as 50 data points for each point, with a time of 2 minutes, with a total of 83 coordinate points, so that the total data collected was 4150, shown in Fig. 5.



(a) **(b)**

(c) **(d)**

Figure 5. Visualization of RSSI Shows the Distribution of Signal Strength in Various Locations within a Room (a) Access Point 1, (b) Access Point 2, (c) Access Point 3, (d) Access Point 4

2.1.3 Measurement Data Testing

Testing of training data from RSSI recording based on Wi-Fi was tested by measuring the test data with a predetermined route, as shown in Fig. 6, at a normal walking speed in general. A predetermined test route was developed to ensure full coverage of indoor areas relevant to the daily activity patterns of older adults, following a pedestrian path that passes through only a few key zones that are passable due to unobstructed areas at normal speeds. The route was traversed to obtain robust and representative test data for evaluation using a Naïve Bayes classifier.

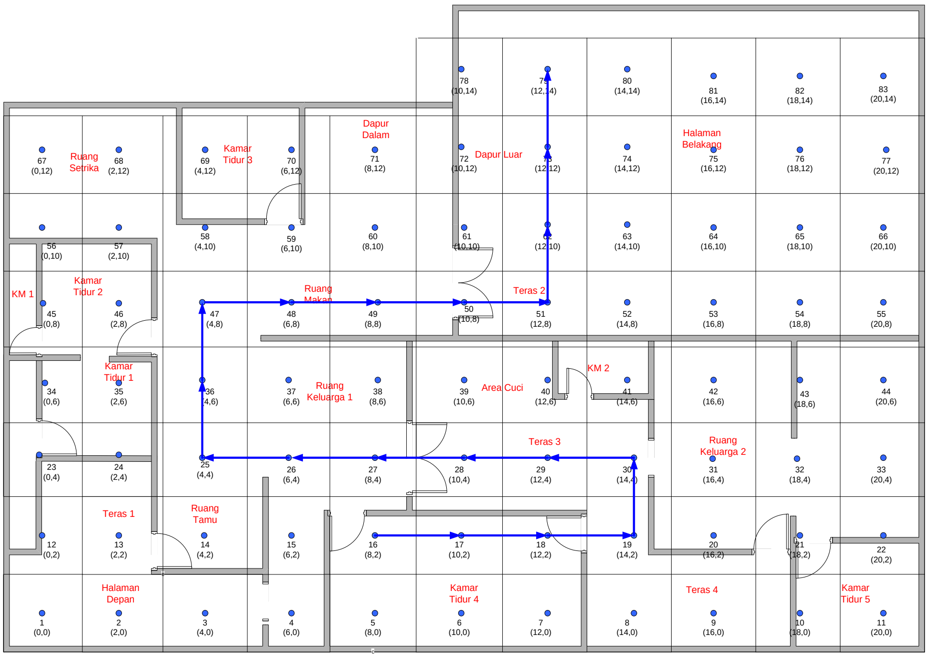
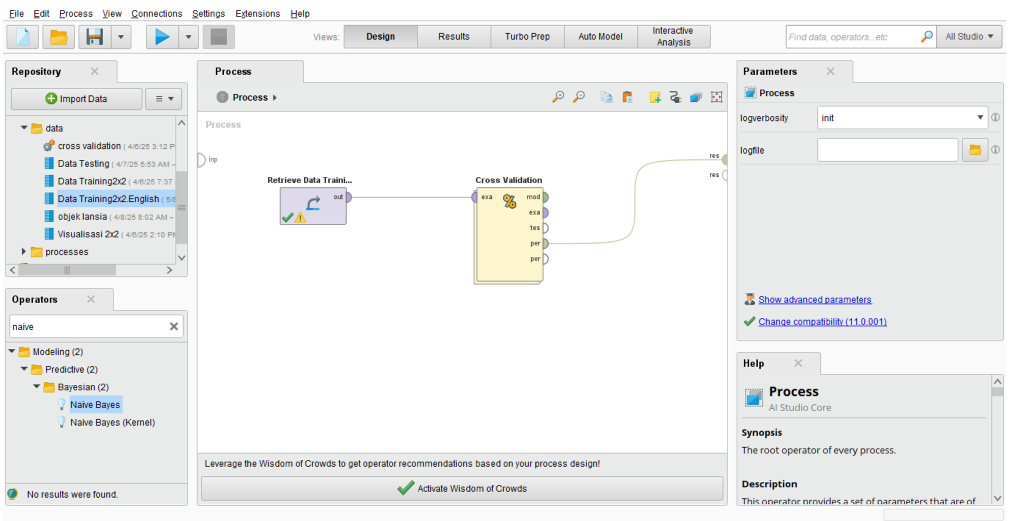


Figure 6. Location of Data Testing

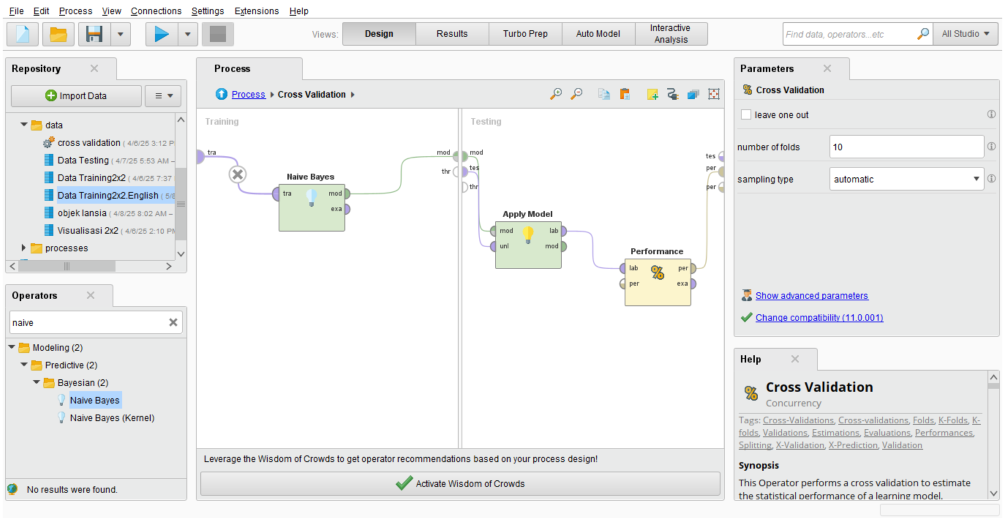
2.1.4 Performance Evaluation

Cross-validation and confusion matrix are techniques that can be used to assess the accuracy of a classification algorithm. Cross-validation is a model by divides the dataset into several training and testing datasets to assess the performance of the specified model. In this study, the cross-validation and confusion matrix using Altair AI Studio 2025 are given in Fig. 7.

This method helps minimize bias and confirm that the model shows strong generalization. To assess the effectiveness of the classification model by comparing model predictions with actual labels using a confusion matrix



(a)



(b)

Figure 7. Accuracy of Naïve Bayes Algorithm
(a) Process, (b) Cross Validation

2.2 Bayesian Classifications

A Bayesian classifier is a statistical classification method that predicts the probability of membership of a tuple to a particular class. It is based on Bayes' Theorem, which is explained below. Several studies comparing classification algorithms have found that a simple Bayesian classifier, known as a Naïve Bayesian classifier, has comparable performance to decision trees and certain neural networks [26]. Bayesian classifiers also show high accuracy and good execution speed when applied to large databases. A Naïve Bayesian classifier assumes that the values of an attribute are independent of other attributes with respect to a particular class. This assumption is called the conditional independence of classes. This assumption is made to simplify the computations involved, and in this sense, is considered "naïve". In contrast to the naive approach, a Bayesian belief network is a graphical model that allows the representation of dependencies between subsets of attributes. These networks can also be used for classification purposes.

To determine the location of the monitored individual, the system applied the Naïve Bayes algorithm. A direct probabilistic technique that relies on Bayesian inference in particular and Bayes' theorem in general, with the strong (naive) independence assumption found in the Naïve Bayes algorithm. In this approach, Naïve Bayes presumes that the existence or lack of a characteristic in a category is independent of the existence or lack of other characteristics in that same category [27]. the independence of the input attribute values in a particular class on the values of other attributes is an assumption of Naïve Bayes [28].

2.2.1 Bayes Theorem

Bayes' theorem is named after Thomas Bayes, a nonconformist English clergyman who in the 18th century did early work on probability and decision theory. Suppose: X is a data tuple (often referred to as "evidence" in Bayesian terms), measured by a set of n attributes. H is a hypothesis, such as "the data tuple X belongs to a certain class C". In a classification problem to determine $P(H|X)$, which is the probability that the hypothesis H holds given the evidence X. In Bayes' theory, to find the probability that tuple X is indeed included in class C, given the description of its attributes. Here are some important terms: $P(H|X)$ is called the posterior probability, which is the probability of the hypothesis H after considering evidence X. (H) is called the a priori probability, which is the probability of H before considering evidence X. $P(X|H)$ is the probability of evidence X if hypothesis H is true. $P(X)$ is the a priori probability of evidence X itself. The probabilities $P(H)$, $P(X|H)$, and $P(X)$ can be estimated from the data.

Bayes' theorem is important because it provides a way to calculate the posterior probability $P(H|X)$ using these three components. The formula for Bayes' Theorem is stated as Eq. (1):

$$P(H|X) = \frac{P(X|H) \times P(H)}{P(X)}. \quad (1)$$

2.2.2 Naïve Bayes Classification

The Naïve Bayesian classifier, or simple Bayesian classifier, works as follows: Let S be a training set of tuples and their associated class labels. As usual, each tuple is represented by an n-dimensional attribute vector, $RSS = (RSS_1, RSS_2, ::: , RSSn)$, depicting n measurements made on the tuple from n attributes, respectively $(AP_1, AP_2, AP_3 , and\ AP_4)$. A set of attribute values in this study is represented by the attribute group S with values $(AP_1, AP_2, AP_3 , and\ AP_4)$. l is the coordinate value, namely point (x, y) and L is the classification variable. From a probability perspective, based on Bayes' rule in class l is written as Eq. (2).

$$P(l|S) = \frac{P(S|l) \times P(l)}{P(S)}. \tag{2}$$

Naïve Bayes assumes that all features Si are independent of each other, given class l then written as Eq. (3).

$$P(S|l) = P(s_1 , s_2 , \ldots, s_n |l) = \prod_{i=1}^{n} P(s_i|l). \tag{3}$$

With this, Bayes' Theorem can be rewritten as Eq. (4).

$$P(l|S) = \frac{\prod_{i=1}^{n} P(s_i|l)\ P(l)}{P(S)}. \tag{4}$$

Mean and standard deviation of the training data set as a representation of signal strength as a Gaussian distribution, and utilizing the collected signal strength to determine the parameters of the Gaussian distribution are required in the NB method. This is obtained by calculating the Euclidean distance of the observed signal vector S located at the position. When the signal strength vector S is derived from the current time measurement of the signal strength in the field, the probability $P(S|l)$ is then calculated for all locations in the field where signal strength was recorded while building the signal strength database, written as Eq. (5). The position l that has the highest probability $P(S|l)$ for the signal strength vector is classified as the user's current field position. M_i^l is the average signal strength APi at position l calculated from the training data written as Eq. (6), D_i^l is the standard deviation of APi at position l calculated from the training data written as Eq. (7) and $|P|$ is the number of AP read at position l.

$$P(S|l) = \prod_{i=1}^{|P|} \left(\frac{1}{\sqrt{2\pi (D_i^l)^2}} \exp\left(-\frac{(S_i - M_i^l)^2}{2(D_i^l)^2} \right) \right), \tag{5}$$

$$M_i^l = \frac{\sum_{i=1}^{n} RSS_i^l}{n}, \tag{6}$$

$$D_i^l = \sqrt{\frac{\sum_{i=1}^{n}(RSS_i^l - M_i^l\ )}{n-1}}. \tag{7}$$

Prediction Location l with the highest posterior probability is selected as the estimation location using formula Eq. (8).

$$l = \arg\max P(S|l). \tag{8}$$

2.3 Calculate the Minimum Average Error Distance

At this stage, the distance between the actual position and the predicted position is calculated in each test data using the formula in Eq. (9), so that the average minimum error distance value is obtained for n test points using the formula in Eq. (10).

$$Error\ Distance = \sqrt{(x_i' - x_i)^2 + (y_i' - y_i)^2} \tag{9}$$

$$Minimum\ Average\ Error\ Distance = \frac{\sum_1^n \sqrt{(x_i' - x_i)^2 + (y_i' - y_i)^2}}{n} \tag{10}$$

2.4 Activity Recognition and Wandering Detection

The objects selected as experimental samples were observed for their daily activities for 24 hours. The collection of location tracking data by comparing previously collected data will form a pattern that is used as a reference to categorize object activities. In individuals exhibiting dementia symptoms, distinct movement patterns are evident as they visit more locations than those without such conditions. In typical situations, they usually dedicate a particular duration to a location and often have a defined reason for being there.

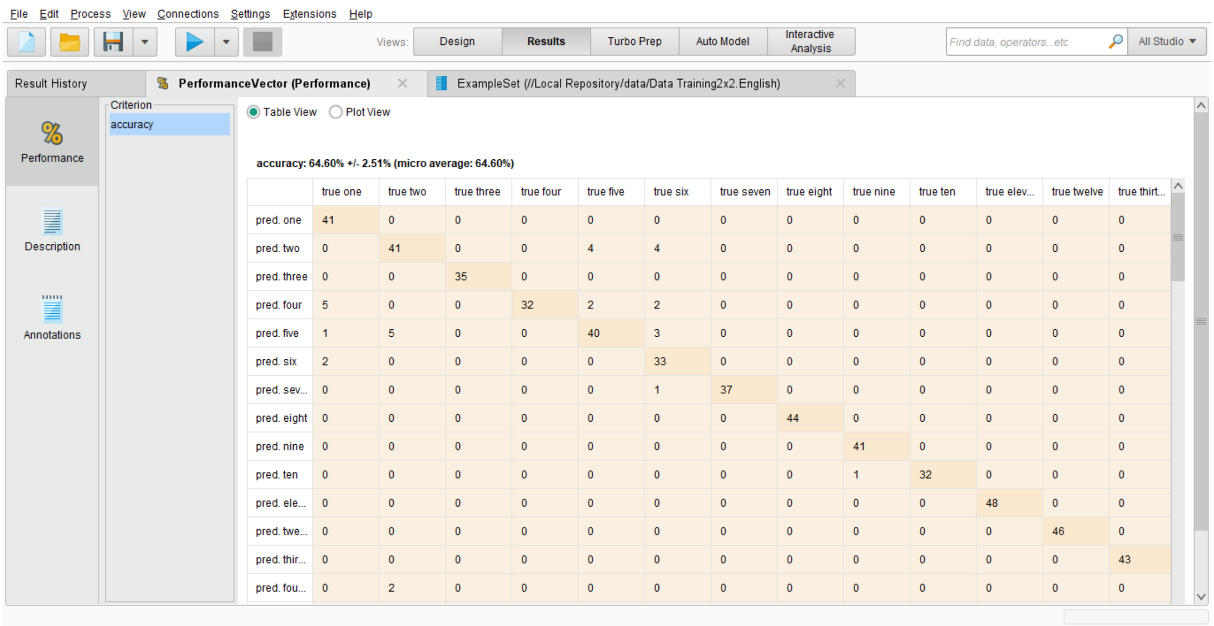
In interpreting these results, it is important to pay attention to various characteristics related to human mobility and travel. Dementia cases characterized by memory loss can result in frequent wandering, although patients appear to seek specific places such as the bedroom, toilet, and dining room. Based on the two characteristics mentioned, there is a clear difference in movement: Movement based on "purpose" in normal circumstances stays in one place for a long period of time. Therefore, adding the time domain to the model for this problem.

3. RESULTS AND DISCUSSION

To assess the precision of the classification algorithm in this research, utilizing Naïve Bayes, techniques that may be employed consist of cross-validation and a confusion matrix. To create applications (development) grounded in models created using Altair AI Studio 2025.

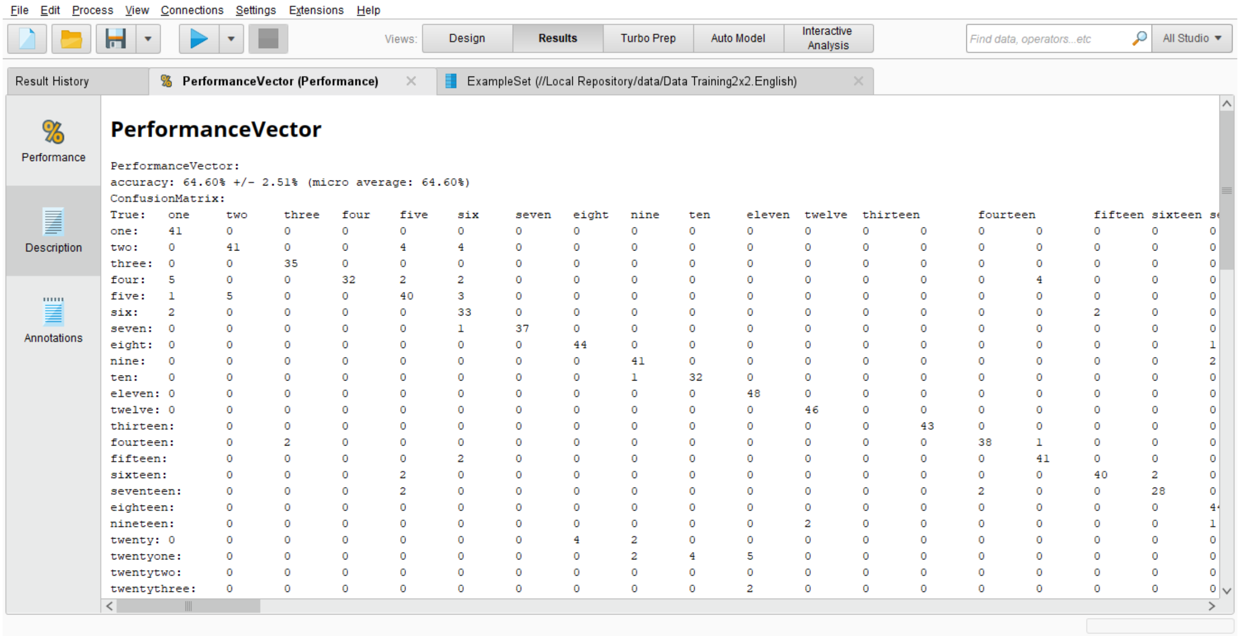
3.1 Performance Evaluation Results

Cross-validation and confusion matrix are used to measure the accuracy of the classification algorithm using Altair AI Studio 2025, as shown in Fig. 8.



	true one	true two	true three	true four	true five	true six	true seven	true eight	true nine	true ten	true elev...	true twelve	true thirt...
pred. one	41	0	0	0	0	0	0	0	0	0	0	0	0
pred. two	0	41	0	0	4	4	0	0	0	0	0	0	0
pred. three	0	0	35	0	0	0	0	0	0	0	0	0	0
pred. four	5	0	0	32	2	2	0	0	0	0	0	0	0
pred. five	1	5	0	0	40	3	0	0	0	0	0	0	0
pred. six	2	0	0	0	0	33	0	0	0	0	0	0	0
pred. sev...	0	0	0	0	0	1	37	0	0	0	0	0	0
pred. eight	0	0	0	0	0	0	0	44	0	0	0	0	0
pred. nine	0	0	0	0	0	0	0	0	41	0	0	0	0
pred. ten	0	0	0	0	0	0	0	0	1	32	0	0	0
pred. ele...	0	0	0	0	0	0	0	0	0	0	48	0	0
pred. twe...	0	0	0	0	0	0	0	0	0	0	0	46	0
pred. thir...	0	0	0	0	0	0	0	0	0	0	0	0	43
pred. fou...	0	2	0	0	0	0	0	0	0	0	0	0	0

(a)



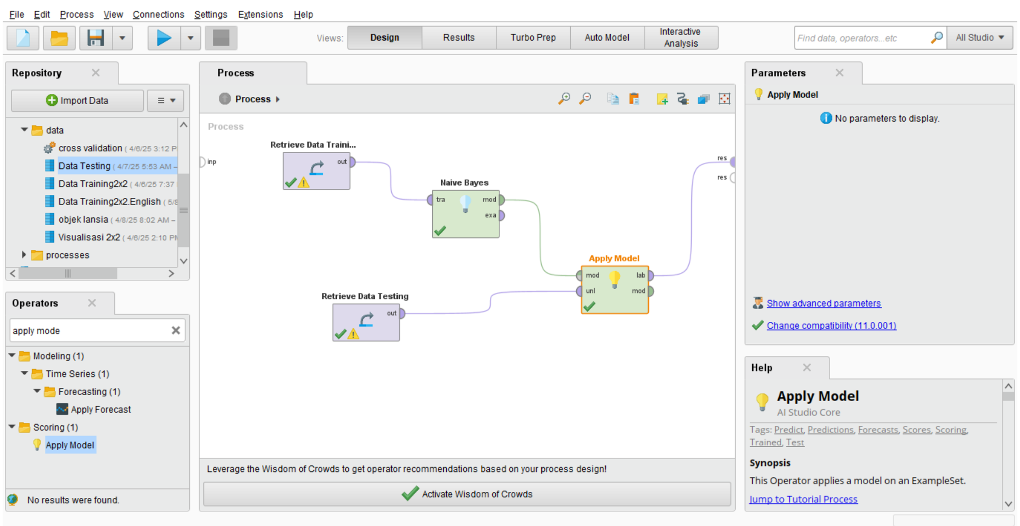
(b)

Figure 8. Accuracy of Naïve Bayes Algorithm
(a) Accuracy (b) Performance Vector

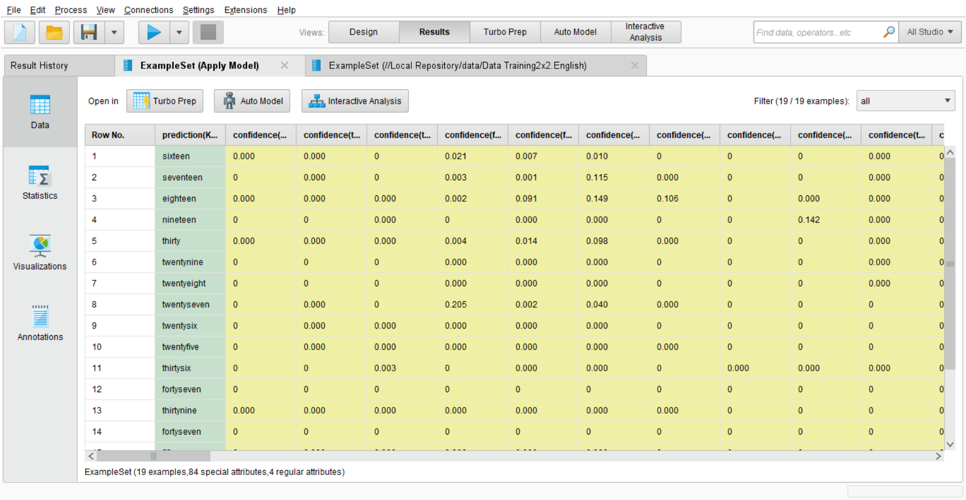
The type of cross-validation used is k-fold cross-validation with the number k being 10. The dataset is divided into 10 parts (folds) of the same size. The results obtained showed a figure of accuracy: 64.60% +/- 2.51% (micro average: 64.60%). 10-fold cross-validation was performed, and the performance vector of the Naïve Bayes classifier was obtained. The average classification accuracy was 64.60%, with a standard deviation of ±2.51%, and the micro-average accuracy was also 64.60%, indicating a reasonably stable performance in classifying indoor activity patterns based on Wi-Fi RSSI data.

3.2 The Minimum Average Error Distance Results

Calculate the minimum average error distance using the formula Eq. (10) and from the modeling results using the Naïve Bayes algorithm given by Fig. 9, the results are shown in Table 1. A value of 0.700 meters was obtained for the minimum average error distance result.



(a)



(b)

Figure 9. Prediction Results with Naïve Bayes Algorithm
(a) Naïve Bayes Design (b) Naïve Bayes Results

The prediction results depicted in Fig. 9 illustrate the classification performance of the Naïve Bayes algorithm for indoor location tracking based on Wi-Fi Received Signal Strength Indicator (RSSI) data. The figure represents the mapping between the predicted locations and the ground truth (actual coordinates), which were used to assess the accuracy and error metrics of the model. The minimum average error distance of the position is determined by computing the distance between the actual and predicted positions, as given in Table 1 below:

Table 1. Minimum Average Error Distance

AP1	AP2	AP3	AP4	Actual Position	x	y	Prediction	x’	y’	Min Error Distance
-44	-92	-90	-100	sixteen	8	2	sixteen	8	2	0
-39	-75	-93	-100	seventeen	10	2	seventeen	10	2	0
-62	-76	-86	-100	eighteen	12	2	eighteen	12	2	0
-71	-59	-78	-100	nineteen	14	2	nineteen	14	2	0
-46	-77	-78	-100	thirty	14	4	thirty	14	4	0
-36	-62	-100	-100	twentynine	12	4	twentynine	12	4	0
-36	-63	-92	-100	twentyeight	10	4	twentyeight	10	4	0
-39	-82	-98	-100	twentyseven	8	4	twentyseven	8	4	0
-71	-91	-100	-100	twentysix	6	4	twentysix	6	4	0
-82	-80	-100	-100	twentyfive	4	4	twentyfive	4	4	0
-71	-54	-86	-100	thirtysix	4	6	thirtysix	4	6	0
100	-65	-80	-100	fortyseven	4	8	fortyseven	4	8	0
-60	-79	-100	-100	fortyeight	6	8	thirtynine	10	6	4.472135955
100	-65	-80	-100	fortynine	8	8	fortyseven	4	8	4
-66	-92	-100	-100	fifty	10	8	fifty	10	8	0
-54	-80	-100	-100	fiftyone	12	8	thirtynine	10	6	2.828427125
-88	-100	-100	-100	fortytwo	12	10	fortyone	10	10	2
-100	-100	-100	-100	thirtythree	12	12	thirtythree	12	12	0
-74	-74	-100	-100	seventynine	12	14	seventynine	12	14	0
Minimum Average Error Distance										**0.700**

The first step is to calculate the average value and standard deviation of each classification. The indoor test environment is divided into a coordinate grid system where each location point represents a classification label. A total of 83 coordinate points are defined as classification centers, ranging from point one (0,0) to point eightythree (20,14). Each coordinate point is spaced 2 meters apart, forming a structured indoor map for location fingerprinting. At each point, RSSI values are collected from 4 Access Points. These RSSI readings represent the features used in the classification task. At every coordinate (point), data collection is performed for 2 minutes at each coordinate point, which produces 50 signal strength data points for each point, and then collected to become training data. During this period, 50 RSSI samples are collected per point. These samples are used to compute to calculate the average value and standard deviation for each AP at each point. Testing data is taken with known points and tested on training data to find out where the prediction results are. From the test data, the probability of being at the location l is calculated using Eq. (2). The largest probability is set as the prediction point.

Then the error distance is calculated using the formula**.** In Table 1, for the prediction data for the thirteenth point sequence that was actually tested, namely point (6,8), but the prediction results show point (10,6). Therefore, there is an error distance of 4.472135955 meters. Therefore, for all tests total of 19 test points using the formula Eq. (6), the minimum average error distance value was 0.700 meters.

3.3 Location Tracking and Wandering Detection

Based on observations of objects for 24 hours using a Wi-Fi RSSI-based sensor to track locations by mapping the training data patterns that have been collected previously, the location tracking results are shown in the following Fig. 10.

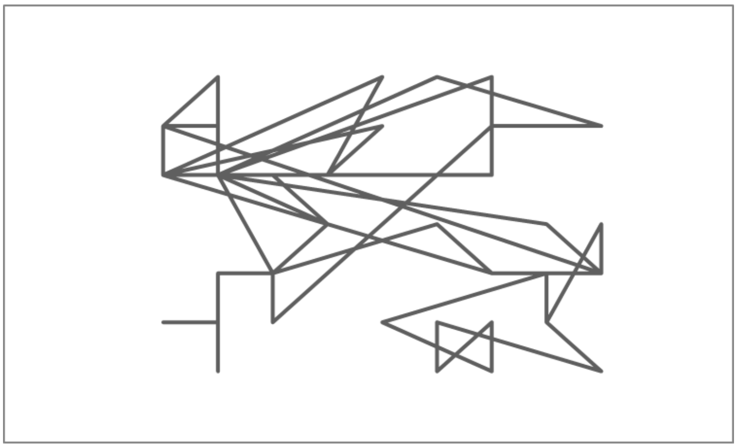


Figure 10. Location Tracking Object

The movement path of the object (subject) within the indoor test environment is illustrated in Fig. 10. The trajectory was estimated based on Wi-Fi RSSI readings collected during the test route, processed through a Naïve Bayes classification model. Each point on the figure corresponds to the predicted location at a given time. The tracking result demonstrates the feasibility of using RSSI-based fingerprinting to monitor object movement and detect anomalous patterns that may indicate wandering behavior associated with early dementia symptoms. From the results of tracking the object coordinate points, it can be seen which rooms the object is in during 24 hours, which can be described by the time graph shown in Fig. 11.

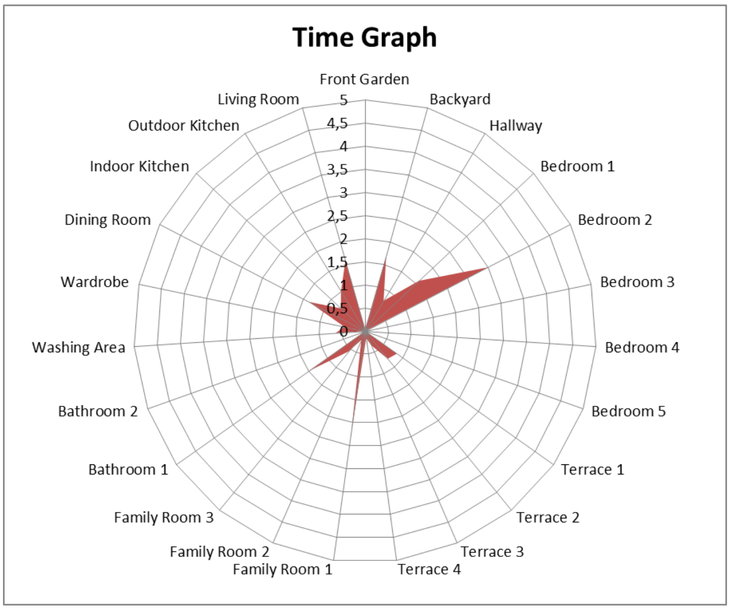


Figure 11. Time Graph Location Object

A pattern of staying at a particular location within an identical time zone, such as Positions further from the center of the circle, indicates more time spent at that location, as shown in Fig. 11. For individuals experiencing wandering symptoms, daily routines are shown as “suspected (wandering) cases” represented by an overall blunt polygon. The ratio of locations visited other than bedroom 2 is higher for wandering cases.

4. CONCLUSION

In this study, we suggest a method for identifying wandering behaviors as a preliminary indication of dementia. In digital activities utilizing Wi-Fi RSSI, we suggest employing the Naïve Bayes algorithm for location tracking and a time graph to identify wandering for the early evaluation of dementia risk. The Naïve Bayes algorithm achieved an accuracy of 64.05% through cross-validation, showing a minimum average error distance of 0.7 meters. In the future, more sophisticated algorithms will be required for the practical application of activity recognition systems to be able to distinguish more activity patterns, such as sitting, walking, and running. High-level activity recognition requires more complex hardware and more sophisticated algorithms. In future work, we plan to integrate machine learning techniques such as Support Vector Machines (SVM) to improve classification performance. Furthermore, sensor fusion combining RSSI data with inertial sensors can improve accuracy and provide a more detailed understanding of user behavior. Real-world deployment and testing with elderly participants will also be conducted to validate the system’s performance and usability in a practical smart home environment.

Author Contributions

Hani Rubiani: Conceptualization, Methodology, Writing-Original Draft, Software, Validation. Eddy Samsolehr: Data Curation, Resources, Draft Preparation. Sulidar Fitri: Formal Analysis, Validation. Muhammad Taufiq: Software, Visualization. Wan Mohd Amir Fazamin: Validation, Writing-Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors have no conflict of interest in reporting the research.

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