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Classification of Elderly's Home Activities using Tree-Based Model

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ABSTRACT

With the aging population, it becomes increasingly essential to prioritize the well-being and safety of older individuals by seeking innovative solutions. One promising approach is the integration of smart home technology equipped with sensors, which can significantly enhance independent living for the elderly. This research centres around the utilization of machine learning techniques to detect and classify activities within smart home environments, specifically focusing on older individuals. By analysing data on their activities and movements, valuable insights can be gained to identify potential behavioural patterns indicating cognitive decline or health issues. The primary goal of the research is to develop robust algorithms capable of accurately identifying and categorizing elderly activities by analysing sensor data collected from various devices. Tree-based approaches, namely Decision Tree and Random Forest, are adopted to achieve their balanced accuracy in categorizing activities and predicting trends and patterns. The results showed that the Random Forest model outperformed the Decision Tree model, achieving a higher balanced accuracy of 69.85% on the training set. This study highlights the immense potential of machine learning in conjunction with smart home technology to significantly improve the lives of the elderly. By accurately identifying and categorizing their activities, caregivers and healthcare professionals can proactively intervene, leading to better outcomes and increased independence for older adults.

1. Introduction

The Department of Statistics Malaysia [1] reported that the elderly population in Malaysia, aged 60 and above, was 3.60 million in the year 2022, and this number is projected to experience a significant increase in the future due to demographic changes. By 2040, it is estimated that the number of elderly individuals in Malaysia will reach 6 million, resulting in a substantial rise in the proportion of the population within this age group. According to Ni *et al.,* [2], the increase in the

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number of older people in society will bring advantages and disadvantages to the world. Some of the strengths of this demographic will shift, with important implications for the nation's public policy, healthcare, and social welfare programs, emphasizing the need for active planning and investment in these areas to ensure the well-being of older populations. However, some disadvantages lead to demographic problems, including the need for effective aged care and support. As the elderly population increases, there is an increasing need for creative solutions to improve the quality of care while promoting freedom and safety [3].

As the increase of the population of people lives longer, the elderly with higher ages will lead to many health issues. Some age-related disorders such as Parkinson's disease, diabetes, cardiovascular disease, Alzheimer's disease, various chronic diseases, and limits in physical functions affect a substantial section of the older population and may affect them more likely [2]. Moreover, some elderly have no access to a phone, causing them to be less able to obtain help in case of emergency [4]. Hence, their children must take care of their parents occasionally to avoid any unexpected accidents. As a result, their children will be chosen to address the challenges of caring for elderly parents or loved ones remotely. Remotely would be the installation of smart home technology to take care of their parents. Another interesting finding by Shamsuddin *et al.,* [5] shows that additive manufacturing can produce an affordable and comfortable prototype of a prosthetic foot using Acrylonitrile Butadiene Styrene (ABS) material and finally help elderly achieve a better quality of life.

In this 21st century, the adoption of smart home systems has increased, enhancing the security and comfort of the elderly by integrating technology into the home [6]. These homes are equipped with sensors and devices that help with the monitoring of elderly activities, in which alerts can be sent to caregivers during emergencies [7]. A smart home-based health monitoring system to analyse the behaviour of diabetic patients has also been implemented by Helal *et al.,* [8], where the food habit is monitored by utilizing the video analysis of chewing motions and the detection of activity if monitored by the sensor. Greene [9] noted that smart home systems were initially costly and limited to wealthier individuals due to complex wired connections. However, with technological progress, affordability increases, causing the extension of accessibility to a wider audience. Smart home technology for the elderly prioritizes safety, independence, and health such that tailored solutions are provided to cater to unique challenges faced by the elderly [10]. Although the smart home system may help monitor elderly activities at home, it may also cause higher energy consumption. According to Rahim *et al.,* [11], the healthcare facility is among the buildings in the world with the highest energy use. Indra and Irfan proposed smart architecture that prioritizes the optimal and efficient use of renewable energy, which is affordable and easy to implement at home [12].

In creating a better smart home environment for the elderly, digital data management plays an important role. By integrating digital data management with smart home systems, caregivers can gain valuable insights into their well-being and provide timely assistance when needed. Furthermore, homeowners can automate routine tasks, adjust settings based on real-time data, and optimize energy efficiency, comfort, and security. An intensive literature review was conducted to identify digital data management approaches used in building’s facility management. According to Wang *et al.,* [13], eight key tools and software such as Computer Aided Facilities Management System, Radio Frequency Identification, Intelligent Building Management System, Intelligent Facilities Management System, Building Information Model, Wireless Sensor Technology, Mobile Intelligent Terminal and technical specification in facility management were identified to be implemented in facility management for high-rise buildings. Ha *et al.,* [14] found that the top three most important factors affecting the public in purchasing a green residence are “improve indoor air quality”, “enhance occupant comfort and health” and “lower greenhouse gases emission”.

Monitoring technologies such as passive infrared (PIR) motion sensors, video monitoring, and sound recognition can help detect activities and important events for a secure living environment [15]. These smart home systems can assist with daily tasks such as medication reminders and voice controls for appliances and offer specialized support for those with mobility or cognitive impairments to maintain their autonomy [2]. Moreover, smart homes for the elderly prioritize health monitoring through various smart devices that track and analyse vital signs, medication adherence, sleep patterns, and activity levels, remotely sharing data with caregivers to enable proactive interventions, personalized care plans, and early identification of health issues [16]. Smart home devices often rely on wireless communication protocols. A design of a dual band coaxial fed microstrip U-shaped antenna is presented by El-Ashmawy and Allam [17]. This design can be effectively used for constructing compact antennas for wireless devices. Through technology integration, smart homes contribute to the overall well-being and improved quality of life for the elderly, allowing secure and comfortable aging in place.

Therefore, machine learning techniques such as Support Vector Machine (SVM), Random Forest, and Decision Trees are applied to recognize high-level activities in a smart home environment. These algorithms identify and classify specific activities performed by the elderly by analysing large data sets, learning from trends, and correlating data. It offers accurate activity recognition systems that empower healthcare professionals, caregivers, and children to ensure timely interventions [18]. Techniques such as Long Short-Term Memory (LSTM) and Logistic Regression have been applied to predict future activities within a smart home context. These methods use sequential data and historical patterns to predict the subsequent actions of the elderly. Usharani and Sakthivel [19] have proposed an Android-based human activity recognition system using accelerometer data for real-time classification. A clustered k-nearest neighbours (k-NN) classifier is used to improve the accuracy and execution time of the k-NN classifier. Anguita *et al.,* [20] also introduced an enhanced SVM algorithm to create an energy-efficient model for classifying human activities using smartphones. Besides, a body-sensor-based activity recognition system for comprehending human behaviour in various settings is introduced by Uddin and Soylu [21], in which LSTM is employed to analyse sensor data. In contrast, Kernel-based Discriminant Analysis (KDA) is used to enhance the clustering of features obtained from different activities.

Although many studies have focused on categorizing human activity using different machine learning techniques, and their accuracy was relatively high due to the adoption of binary classification, there have been few studies on the effectiveness of machine learning approaches for a more significant number of classes. This research gap limits the understanding of the performance of machine learning techniques in a multi-class classification compared to a binary classification. Therefore, this research aims to study the application of tree-based machine learning methods using a nine-class activity approach for recognizing and monitoring elderly activities in smart homes. The study seeks to develop a prototype system for real-time activity monitoring and reporting in smart homes through a comprehensive analysis of existing approaches, data collection, pre-processing, and evaluation of machine learning algorithms. By bridging the gap between advanced computing and aged care, the results seek to improve the overall well-being, safety, and independence of the elderly while lowering the pressures on caregivers and healthcare. The research objectives encompass the development of data-cleaning techniques, visualization of elderly activity patterns, and a comparative assessment of tree-based machine learning models for classifying home activities. Ultimately, this work strives to facilitate anomaly detection and anticipate future actions, contributing to innovative solutions in aged care and smart home support systems.

2. Methodology
2.1 Dataset

The ARUBA dataset from the Centre for Advanced Studies in Adaptive Systems (CASAS) was used in this study. This dataset comprises 7-month sensor data collected from 4 November 2010 to 11 June 2011 in the smart home of an elderly woman. There are 1,719,558 observations and six variables in the dataset. The house consists of 31 binary motion sensors (sensor IDs begin with "M"), five temperature sensors (sensor IDs begin with "T"), and 4 door sensors (sensor IDs begin with "T"), which are used to generate the sensor data when a movement is detected. For this research, only door and motion sensors are used, whereas temperature sensors are not considered as they vary primarily based on seasonal changes, and it was deemed irrelevant for this research. Besides, one door sensor is never recognized. Hence, only 34 sensors are utilized for this study.

Table 1 shows the first ten observations of the dataset before any data cleaning is done. The variable columns are renamed to *Date, Time, Sensor, SensorStatus, Activity*, and *BeginEnd*.

Table 1
First 10 observations before cleaning

	X1	X2	X3	X4	X5	X6
1	2010-11-04	00:03:50	M003	ON	Sleeping	Begin
2	2010-11-04	00:03:57	M003	OFF	NA	NA
3	2010-11-04	00:15:08	T002	21.5	NA	NA
4	2010-11-04	00:30:19	T003	21	NA	NA
5	2010-11-04	00:30:19	T004	21	NA	NA
6	2010-11-04	00:35:22	T005	20.5	NA	NA
7	2010-11-04	00:40:25	T005	21	NA	NA
8	2010-11-04	00:45:28	T005	20.5	NA	NA
9	2010-11-04	01:05:42	T001	20	NA	NA
10	2010-11-04	01:15:48	T002	21	NA	NA

Table 2 shows the eleven types of activities done by the elderly woman. It is observed that the *Activity* variable contains a large number of missing values, which is represented by the NAs. Therefore, it is advisable to remove these entries to ensure accurate predictions due to the significant amount of missing data. It is noted that the *Respirate* activity has a low frequency of 12 occurrences. Given its low frequency and the fact that respiration is a continuous and essential bodily function, it is concluded that this activity does not contribute meaningful insights to the analysis. As a result, the observations for *Respirate* are removed.

Table 2
Frequency of *Activity* before cleaning

Bed_to_Toilet	Eating	Enter_Home	Housekeeping	Leave_Home	Meal_Preparation
314	514	862	66	862	3212
Relax	Respirate	Sleeping	Wash Dishes	Work	NA's
314	514	862	66	862	3212

2.1 Data Pre-Processing

The data cleaning process is mandatory to produce a more accurate predictive model to address issues with incorrect, corrupted, improperly formatted, and duplicated data within the dataset. Data visualization will also be more valuable and insightful when the dataset is being cleaned. Firstly, upon importing the dataset, the dataset is checked for duplications. Any duplicated entries are eliminated to ensure that the dataset contains only the unique observations. Additionally, the time format within the dataset is modified to the Hours: Minutes: Seconds format for a better representation of time.

Table 3 shows the number of observations detected by each Sensor variable. It is noticed that “ENTERHOME” and “LEAVEHOME” are incorrectly labelled as sensors, and since there are only five observations in total for both categories, these observations are removed. These observations are likely errors or anomalies in the data. Specific observations, such as observations for M030 and M016, are also eliminated as they did not record any observations and provide valuable information for the analysis. From the floor plan, the sensors M030 and M016 are near the door sensors D002 and D004. Thus, using the door sensors to classify the activity rather than the motion sensor is more valuable. Furthermore, the temperature sensors (IDs that begin with “T”) will also be removed. Since the temperature in the smart home ranges between 16 and 43 degrees Celsius and varies primarily based on seasonal changes, the temperature data is deemed irrelevant for this research.

Table 3
Number of observations detected by each *Sensor* variable

c	D001	D002	D004	ENTERHOME	LEAVEHOME	M001
1	519	413	5904	1	4	12177
M002	M003	M004	M005	M006	M007	M008
9553	40682	20055	35563	27373	94099	35513
M009	M010	M011	M012	M013	M014	M015
263489	47601	4051	30370	86663	89185	98320
M016	M017	M018	M019	M020	M021	M022
29635	49946	82256	157833	162204	46509	31029
M023	M024	M025	M026	M027	M028	M029
12551	57293	4959	25457	14817	7817	7782
M030	M031	T001	T002	T003	T004	T005
8511	2851	16601	26224	26418	20193	27136

There are some observations has the incorrect spellings of "OFF", "CLOSE", "ON", and "OPEN" ("O", "OF", …) in the *SensorStatus* variable. The incorrect spellings are replaced with the proper spelling. Later, incorrect labels are also identified in this variable. For instance, the corresponding sensor should be in an "ON" state when an activity begins. However, some entries are incorrectly indicated as "OFF". To rectify this, modifications were made to ensure that the *SensorStatus* variable accurately reflected the state of the activity.

Table 4 shows the ARUBA dataset's descriptive statistics, including each variable's names and descriptions. To gain further insights on the patterns of activities performed by the elderly woman in a week, a new column named *Day* is added. A *DateTime* variable is also created by merging the *Date* and *Time* variables to easily calculate each activity's duration later on. Then, the variable columns are rearranged, following the order: *Day, Sensor, SensorStatus, Activity, BeginEnd,* and *DateTime*.

Table 4
Descriptive statistics of the ARUBA dataset

Variable	Description
Day	Day (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday)
Sensor	31 Motion Sensors (IDs begin with “M”) and 3 Door Sensors (IDs begin with “D”)
SensorStatus	4 categories of sensor status (OPEN, CLOSE, ON, OFF)
Activity	10 Activities done by the elderly in the smart home environment (*Bed_to_Toilet, Eating, Enter_Home, Housekeeping, Leave_Home, Meal_Preparation, Relax*, *Sleeping, Wash Dishes, Work*)
BeginEnd	Indication of the begin and end of each activity
DateTime	The merging of *Date* (Year-Month-Day) and *Time* (Hours-Minutes-Seconds) variables

Figure 1 shows the frequency distribution of the *Activity* variable after the data cleaning process. Since the *Enter_Home* activity corresponds to the *Leave_Home* activity, the number of observations for both activities should be tallied. It is observed that this result is achieved after the data cleaning, and both activities can now be merged to calculate the duration of the elderly woman is away from home. The duration of other activities is also calculated.

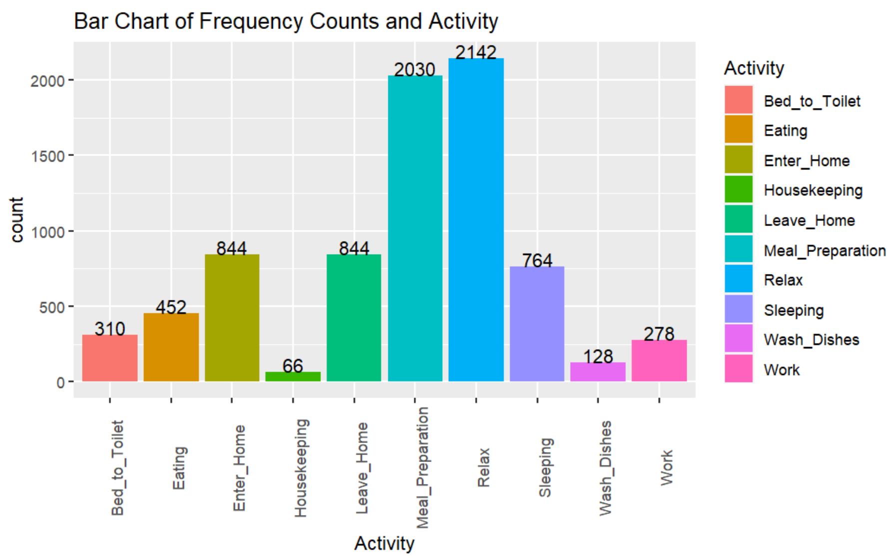

Fig. 1. Frequency distribution of the *Activity* after the data cleaning process

Table 5 displays the first ten observations after the data pre-processing. The dataset now contains 3,507 observations and five variables for further analysis. Ultimately, by performing these data cleaning and modification steps, the dataset was refined to ensure the accuracy and reliability of the information about the relevant activities and variables, thus improving the quality of subsequent analysis.

Table 5
First 10 observations after pre-processing

	Day	Activity	BeginTime	EndTime	Duration
1	Thursday	Sleeping	2010-11-04 00:03:50	2010-11-04 05:40:43	05:36:53
2	Thursday	Bed_to_Toilet	2010-11-04 05:40:51	2020-11-04 -5:43:30	00:02:39
3	Thursday	Sleeping	2010-11-04 05:43:45	2010-11-04 08:01:12	02:17:27
4	Thursday	Meal_Preparation	2010-11-04 08:11:09	2010-11-04 08:35:45	00:24:36
5	Thursday	Relax	2010-11-04 09:29:23	2010-11-04 09:34:05	00:04:42
6	Thursday	Housekeeping	2010-11-04 09:34:16	2010-11-04 09:44:40	00:10:24
7	Thursday	Meal_Preparation	2010-11-04 09:48:52	2010-11-04 09:56:27	00:07:35
8	Thursday	Eating	2010-11-04 09:56:41	2010-11-04 10:02:48	00:06:07
9	Thursday	Wash_Dishes	2010-11-04 10:03:21	2010-11-04 10:04:25	00:01:04
10	Thursday	Housekeeping	2010-11-04 11:29:08	2010-11-04 11:33:48	00:04:40

2.3 Model

Machine learning techniques like Decision Tree and Random Forest are frequently used for categorizing and predicting data in both classification and regression applications. Each of these methods possesses unique advantages and limitations. Decision Tree and Random Forest selection rely on several factors, such as the problem's complexity, dataset size and characteristics, interpretability needs and the balance between accuracy and computational demands. Before settling on a prediction model and proceeding with research objectives, exploring various algorithms and assessing their performance using appropriate evaluation metrics for comparison is prudent.

2.3.1 Decision tree

A Decision Tree is a hierarchical model used for decision-making that represents options and their potential outcomes in a tree-like structure. It considers factors such as utility, resource costs, and chance event outcomes [22]. The label of a leaf node indicates the predicted class of the instance when encountered [23]. Decision Tree provides an intuitive and interpretable approach to decision-making in various domains.

The initial step entails creating a Decision Tree on the ARUBA dataset and applying the Decision Tree method using an appropriate implementation. The dataset was partitioned iteratively based on different attributes by the Decision Tree to increase the goal of increasing information gain or decreasing impurity at each node. The splitting criteria and node creation for the dataset are then taken into consideration. The dataset was split using recursive splitting, producing child nodes and branching out the tree according to the chosen splitting criterion. This procedure is continued until a stopping criterion is satisfied, such as a maximum depth, a minimum number of samples per leaf or a predetermined threshold for impurity reduction.

Besides, the Decision Tree may optionally be pruned to reduce overfitting. Pruning entails eliminating or collapsing nodes that do not make a meaningful contribution to the correctness of the tree as a whole. This enhances the model's ability to generalize to new data. Lastly, the Decision Tree model's performance on the test set is assessed. To evaluate how well the Decision Tree predicts the outcomes, assessment metrics like accuracy, precision, recall, or F1 score are considered.

$$\text{Entropy} = -\sum_{i=1}^{n} p_i \log_2 \left(p_i \right) \quad (1)$$

$$\text{Information Gain}\left(\text{IG}\right)=\text{Entropy}\left(\text{parent}\right)-\text{Average Entropy}\left(\text{children}\right) \quad (2)$$

$$\text{Gini Index}\left(\text{GI}\right)=1-\sum_{i=1}^{n} p_i^2 \quad (3)$$

2.3.2 Random forest

The Random Forest is a classification system composed of multiple decision trees. It aims to create a collection of uncorrelated trees where the collective prediction outperforms any individual tree. This is achieved through bagging and variable randomness during the creation of each tree. The final classification outcome is determined by aggregating the results of these votes. Random Forest is known for their high accuracy in classification tasks, robustness against noise and outliers as well as the avoidance of overfitting issues [24].

To maximize performance on the ARUBA dataset, the hyperparameters of the Random Forest have been fine-tuned. The number of trees, the number of characteristics considered at each split, and the maximum depth of the trees are examples of common hyperparameters. The cross-validation method has been applied in order to identify the ideal hyperparameter values. Understanding which variables are most significant for the current ARUBA dataset can be done by considering variable importance. Once the Random Forest model has been developed, tested, and optimized on the ARUBA dataset, it may be applied to forecast new, unforeseen data occurrences.

2.4 Model

In machine learning research or applications, the evaluation of models plays a critical role in assessing their performance. Various assessment metrics and methodologies are employed for model evaluation, depending on the specific type of model being assessed and the nature of the problem at hand. Confusion matrices are the commonly used technique to analyse the model's performance in depth for each class and can point out potential areas for development. Table 6 shows the definition of the commonly used terms in the context of the binary classification.

Table 6
Definition of Confusion Matrix Elements

Element	Definition
True Positive (TP)	The outcome in which the model accurately predicts the number of positive class activities.
True Negative (TN)	The outcome in which the model accurately predicts the number of negative class activities.
False Positive (FP)	The outcome in which the model incorrectly predicts the number of negative class activities as positive.
False Negative (FN)	The outcome in which the model incorrectly predicts the number of positive class activities as negative.

Several inaccuracies were identified in the model's outputs, particularly in predicting certain activities. For instance, the activity *Meal_Preparation* was incorrectly associated with *Bed_to_Toilet*, *Eating, Enter_Home, Housekeeping, Leave_Home, Relax, Sleeping, Wash_Dishes* and *Work*. Each of these activities exhibited errors, and the evaluation of the activity recognition will involve assessing various metrics such as Sensitivity (Recall), Specificity, Positive Predictive Value (Precision), Negative Predictive Value (NPV), F1-Score, Accuracy and Balanced Accuracy.

$$\text{Sensitivity}\left(\text{Recall or True Positive Rate}\right)=\frac{\text{TP}}{\text{TP+FN}} \tag{4}$$

$$\text{Specificity}\left(\text{True Negative Rate}\right)=\frac{\text{TN}}{\text{TN+FP}} \tag{5}$$

$$\text{Balanced Accuracy}=\frac{\text{Sensitivity}\times\text{Specificity}}{2} \tag{6}$$

3. Results

This section involves interpreting collected data using statistical techniques to draw meaningful conclusions, including summary statistics, measure analysis, and hypothesis testing. It aims to visualize the activity patterns of the elderly and compare the capability of tree-based machine learning models in activity classification and prediction.

The evaluation demonstrates the effectiveness of the Decision Tree model and Random Forest model in detecting the activity of the elderly in smart homes. A model with a high accuracy rate indicates that it can effectively recognize various activities. Both models have a balanced performance in accurately recognizing positive cases and minimizing false positives and negatives, according to the model's precision and recall scores. Through confusion matrix analysis, specific activities that are vulnerable to misclassifications can be identified. The results of this research offer an automatic and trustworthy activity recognition system, which advances the field of senior care in smart homes.

3.1 Data Analysis

Data analysis was performed on the cleaned dataset to identify any possible patterns in the daily activities carried out by the elderly woman so that the routines and behaviours of the elderly woman can be examined.

Figure 2 shows the frequency count of *Activity* done by the elderly in the smart home environment. One of the most frequent activities done by the elderly woman is *Relax*, with the highest count of 166 times on Tuesday and the lowest count of 141 times on Wednesday. Other than the *Relax* activity, the most frequent activity done by the elderly woman is *Meal_Preparation*, with the highest count of 170 times on Tuesday and the lowest count of 121 times on Wednesday. This indicates that the elderly woman is more relaxed and has more desire to prepare meals on Tuesday, while less relaxed and less desire to prepare meals on Wednesday.

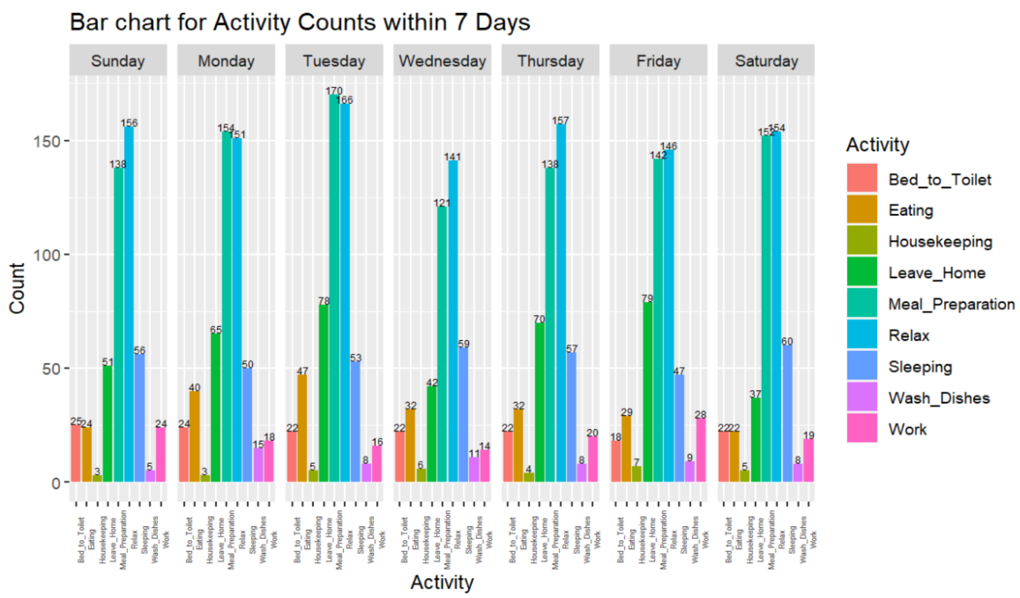

Fig. 2. Bar chart of frequency counts of *Activity* within 7 days

Table 7 shows the nine activities extracted from the dataset. To facilitate the model development and evaluation process, the data was divided into a training set comprising 70% of the observations and a test set comprising the remaining 30%. This partitioning resulted in 2,460 observations allocated to the training set and 1,047 observations to the test set.

Table 7
Nine activities with k = 9

k	*Activity*
1	*Bed_to_Toilet*
2	*Eating*
3	*Housekeeping*
4	*Leave_Home*
5	*Meal_Preparation*
6	*Relax*
7	*Sleeping*
8	*Wash_Dishes*
9	*Work*

The training set data was utilized to explore the characteristics of the data and build suitable models while the testing set data was employed to evaluate and compare the performance of candidate models. A summary of the training and testing samples used in this report is shown in Table 8.

Table 8
Nine activities with k = 9

Class	1	2	3	4	5	6	7	8	9	Total
Train	109	159	24	296	711	750	268	45	98	2460
Test	46	67	9	126	304	321	114	19	41	1047
Total	155	226	33	422	1015	1071	382	64	139	3507

3.2 Modelling
3.2.1 Decision tree

Figure 3 illustrates the final Decision Tree model undergoing the prediction process. A total of 10 splits occurs between the nine activities performed by the elderly woman. A root node of *Relax* activity had been chosen as the first split based on the Duration of seconds. In the Decision Tree model, some *Activity* variables are used for prediction, but some are not. As shown in the figure above, *Bed_to_Toilet, Leave_Home, Meal_Preparation, Relax* and *Sleeping* are used due to their large observation counts. The variables were derived based on the importance of *Duration* and *BeginTime*, resulting in the creation of 11 distinct leaf nodes that represent the activities of *Bed_to_Toilet, Meal_Preparation, Leave_Home, Relax*, and *Sleeping*.

The first split of the Decision Tree with the highest CP value of 0.2456 indicates a simpler tree, whereas the ninth split with a lower CP value of 0.0105 indicates a more complex tree. This split also shows a high relative error value of 1.0, indicating that most variance is explained during the split. The proportion of variance is explained by the split decreases as the number of splits increases.

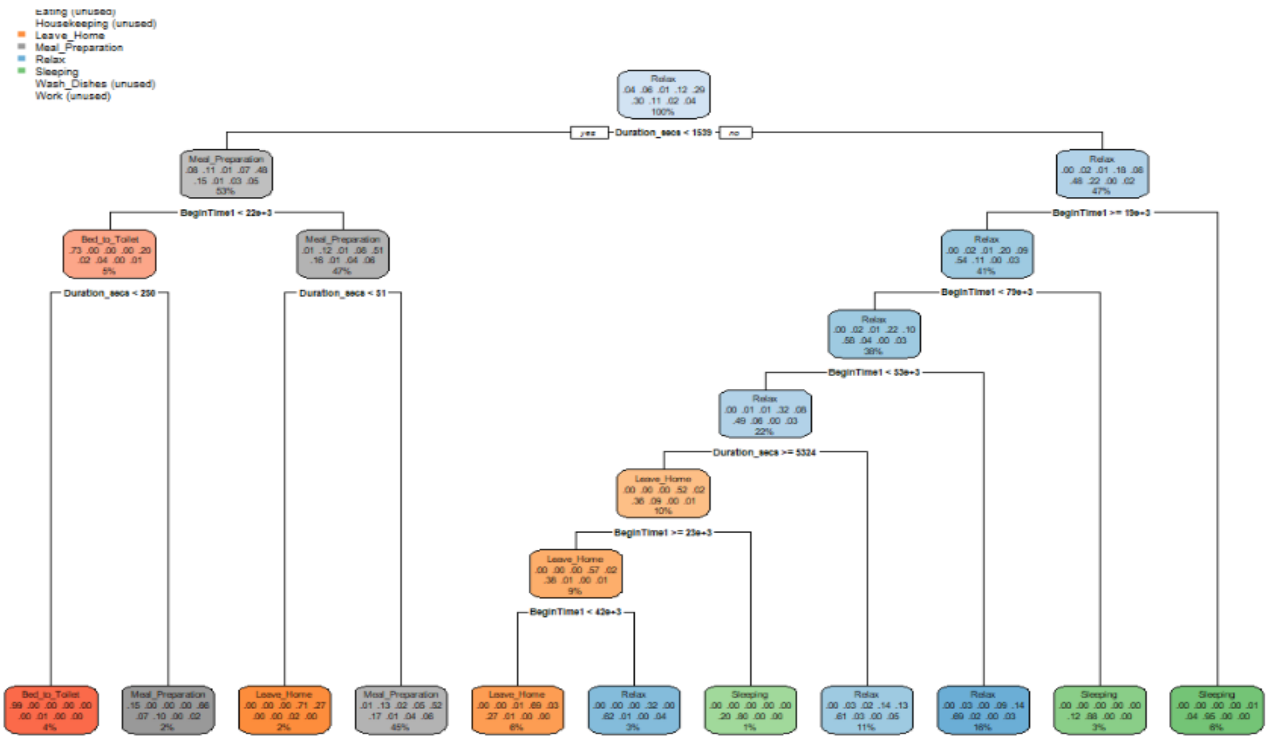

Fig. 3. Decision Tree model

Table 9 represents the classification results for the Decision Tree model trained on a training set. It shows the predicted activities on the vertical axis and the actual activities on the horizontal axis. Each cell in the table represents the count of instances where the predicted activity matches the actual activity. It also provides an overview of the model's performance in predicting different activities based on the training set. It shows the number of correct predictions and misclassifications for each activity, which can help assess the model's accuracy and identify areas where it may need improvement. It shows that most observations are predicted towards the *Meal_Preparation* and *Relax* activities.

Table 9
Confusion matrix of the training dataset for the Decision Tree model

		1	2	3	4	5	6	7	8	9
Predicted	1	92	0	0	0	0	0	1	0	0
	2	0	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0	0
	4	0	0	1	138	16	43	1	1	0
	5	17	140	17	61	603	194	14	42	70
	6	0	19	6	97	92	492	17	2	28
	7	0	0	0	0	0	21	235	0	0
	8	0	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0	0

Table 10 provides the overall statistics of the Decision Tree model using a training dataset that classifies an elderly woman's home activities. The accuracy of this model correctly predicts home activities by approximately 63.41%. The Kappa value is a measure of agreement between the predictions of the model and the actual home activities, accounting for the agreement occurring by chance. A kappa value of 0.5108 indicates a moderate level of agreement beyond chance.

Table 10
Overall statistics of the Decision Tree model using the training dataset

Overall Statistics	
Accuracy	0.6341
95% Confidence Interval	(0.6148, 0.6532)
No Information Rate (NIR)	0.3049
P-Value [Acc > NIR]	$< 2.2 \times 10^{-16}$
Kappa	0.5108

Table 11 shows the summary statistics by class for the training dataset for the Decision Tree model. The sensitivity of the model achieves from 0 to 0.8769 for different activities. The highest sensitivity value of 0.8769 at $k = 7$ indicates a better performance in correctly identifying the *Sleeping* activity. The balanced accuracy value calculates the average of sensitivity and specificity, providing an overall performance measure. The balanced accuracy values range from 0.5 to 0.9334. The highest balanced accuracy value of 0.9334 at $k = 7$ indicates that the *Sleeping* activity gets a better classification performance.

Table 11
Summary of statistics by class on the training dataset for the Decision Tree model

	1	2	3	4	5	6	7	8	9
Sensitivity	0.8440	0.0000	0.0000	0.4662	0.8481	0.6560	0.8769	0.0000	0.0000
Specificity	0.9996	1.0000	1.0000	0.9713	0.6827	0.8480	0.9900	1.0000	1.0000
Balanced Accuracy	0.9218	0.5000	0.5000	0.7188	0.7654	0.7520	0.9334	0.5000	0.5000

Table 12 generates the overall statistics of the Decision Tree model using the testing dataset. The accuracy of this model correctly predicts home activities for approximately 60.65%. Hence, the statistics suggest that the machine learning model used for classifying home activities achieves an accuracy significantly higher than the no-information rate, indicating its effectiveness.

Table 12
Overall statistics of the Decision Tree model using the testing dataset

Overall Statistics	
Accuracy	0.6065
95% Confidence Interval	(0.5762, 0.6362)
No Information Rate (NIR)	0.3066
P-Value [Acc > NIR]	< 2.2×10^{-16}
Kappa	0.4704

The sensitivity values range from 0 to 0.8684. This means that the *Sleeping* activity has a high chance to be correctly classified with its sensitivity value being 0.8684 at k = 7. The balanced accuracy ranges from 0.5 to 0.9283. The highest balanced accuracy value of 0.9283 at k = 7 indicates a reasonable level of accuracy in classifying observations belonging to *Sleeping*.

3.2.2 Random forest

In this machine-learning model, the dataset is split and utilized once again. The model generated predictions that closely resembled those obtained from the previously trained dataset. 500 trees with a binary split are used for this Random Forest model.

Table 13 shows the classification results for the Random Forest model trained on a training set with the class error. The class error is also known as classification error or misclassification error by measuring the proportion of incorrectly classified instances in a dataset. It indicates how well the model fits or predicts the class labels of the training dataset. A low-class error of 0.0826 for k = 1 (*Bed_to_Toilet*) variable indicates an accurate classification and a good fit to the data, in which the underlying patterns are captured. Conversely, a high-class error of 0.9592 for k = 9 (*Work*) variable suggests an incorrect classification and potential issues like underfitting or overfitting.

Analysing the confusion matrix can help identify specific areas where the model is performing well or struggling. It should be concluded that the higher the diagonal values of the confusion matrix, the better, indicating a large number of correct predictions. Most of the observations fall under the *Relax* and *Sleeping* activities.

Table 13
Confusion matrix of the training dataset for the Random Forest model

		1	2	3	4	5	6	7	8	9	class.error
Predicted	1	100	0	0	0	9	0	0	0	0	0.0826
	2	0	36	0	1	91	28	0	2	1	0.7736
	3	0	4	1	4	6	9	0	0	0	0.9583
	4	0	4	1	144	40	103	0	0	4	0.5135
	5	5	37	2	14	517	126	1	2	7	0.2729
	6	0	21	1	56	155	500	9	1	7	0.3333
	7	1	1	0	1	9	15	241	0	0	0.1007
	8	0	8	1	2	28	2	0	3	1	0.9333
	9	0	4	0	2	53	32	1	2	4	0.9592

Table 14 represents the overall statistics of the Random Forest model using the training dataset. It typically includes various performance metrics that summarize the model's predictive capabilities and the fit to the training data and also provide insights into the model's training performance but should be considered in conjunction with other evaluation metrics and validation datasets for a comprehensive understanding of the model's effectiveness. The accuracy of this model correctly predicts home activities by approximately 62.85%.

Table 14
Overall statistics of the Random Forest model using the training dataset

Overall Statistics	
Accuracy	0.6285
95% Confidence Interval	(0.6090, 0.6476)
No Information Rate (NIR)	0.3049
P-Value [Acc > NIR]	$< 2.2 \times 10^{-16}$
Kappa	0.5142

Table 15 shows the summary of statistics by class on the training dataset for the Random Forest model. The sensitivity of the model ranges from 0.0408 to 0.9174 for different activities. The highest sensitivity value of 0.9174 at k = 1 indicates a better performance in correctly identifying the *Bed_to_Toilet* activity. The balanced accuracy provides an overall measure of the model's performance, accounting for both positive and negative instances. The balanced accuracy values range from 0.5162 to 0.9574. The highest balanced accuracy value of 0.9574 at k = 1 indicates that the *Bed_to_Toilet* activity gets a better classification performance.

Table 15
Summary of statistics by class on the training dataset for the Random Forest model

	1	2	3	4	5	6	7	8	9
Sensitivity	0.9174	0.2264	0.0417	0.4865	0.7271	0.6667	0.8993	0.0667	0.0408
Specificity	0.9975	0.9657	0.9979	0.9630	0.7764	0.8158	0.9950	0.9971	0.9915
Balanced Accuracy	0.9574	0.5960	0.5198	0.7248	0.7518	0.7412	0.9471	0.5319	0.5162

Table 16 represents the overall statistics of the Random Forest model using the testing dataset. The accuracy of 60.74% is detected for the predictions when using the tested dataset. The high accuracy shows that the prediction is to be reliable.

Table 16
Overall statistics of the Random Forest model using the testing dataset

Overall Statistics	
Accuracy	0.6074
95% Confidence Interval	(0.5771, 0.6372)
No Information Rate (NIR)	0.3066
P-Value [Acc > NIR]	$< 2.2 \times 10^{-16}$
Kappa	0.4847

The sensitivity values range from 0 to 0.8947. This means that the *Sleeping* activity has a high chance to be correctly classified with its sensitivity value being 0.8947 at k = 7. The balanced accuracy ranges from 0.4980 to 0.9452. The highest balanced accuracy value of 0.9452 at k = 7 indicates a reasonable level of accuracy in classifying observations belonging to *Sleeping*.

Variable importance measures in a Random Forest model provide insights into the relative importance or contribution of each variable in predicting the target variable. These measures help identify which variable has the most significant impact on the model's predictions. The *Duration* variable has the highest variable importance measure on k = 1 (*Bed_to_*Toilet) and k = 7 (*Sleeping*), which are 135.1517 and 144.9530 respectively. Both of these activities are most important for this model for the elderly that lives in the smart home environment.

Other than that, mean decrease accuracy provides relative importance measures for variables in the Random Forest model. A higher value indicates a more influential variable in terms of accuracy or impurity reduction. The *Duration* variable shows an extremely high mean decrease accuracy of 233.8829.

The summary of the comparative assessment of tree-based machine learning techniques for categorizing household activities of the elderly woman is presented here. Comparing the Tables 17 and 18, it appears that the accuracy and balanced accuracy values for the Decision Tree model and Random Forest model are somewhat similar. However, the Random Forest model seems to perform slightly better than the Decision Tree model in terms of accuracy and balanced accuracy on both the train and test sets.

In terms of accuracy, the Random Forest model achieves a higher accuracy on the test set with 60.74%, followed by the Decision Tree model with 60.65%. For the train set, the Decision Tree model has a higher accuracy with 63.41%, followed by the Random Forest model with 62.85%.

Table 17
Summary of the accuracy of the predicted model

Model	Accuracy (%)	
	Train Set	Test Set
Decision Tree	63.41	60.65
Random Forest	62.85	60.74

When considering the balanced accuracy that takes into account the class imbalances, the Random Forest model again performs better. It achieves a higher balanced accuracy on the test set with 68.31%, followed by the Decision Tree model with 65.57%. For the train set, the Random Forest model also has a higher balanced accuracy with 69.85%, followed by the Decision Tree model with 67.68%. Overall, it seems that the Random Forest model has a better performance compared to the Decision Tree model in the terms of accuracy and balanced accuracy.

Table 18
Summary of the balanced accuracy of the predicted model

Model	Balanced Accuracy (%)	
	Train Set	Test Set
Decision Tree	67.68	65.57
Random Forest	69.85	68.31

3.3 Discussion

This research focused on understanding and predicting the behaviour of elderly individuals living in a smart home environment for seven months. One of the research objectives is to improve the dataset's quality by addressing issues like missing values, outliers, noise, and measurement inconsistencies through effective data-cleaning techniques, enable the visualization, and pattern of the dataset and compare the performance of different machine learning models in classifying elderly home activities. The machine learning methods, specifically Decision Tree and Random Forest, have been used to classify the activities performed by the elderly.

Interestingly, the research's findings differed from previous research on activity recognition in smart homes. Past studies using SVM, One-Class SVM, PNN, and K-means clustering achieved high-performance levels of 88% to 95% on the CASAS Aruba dataset [18]. However, the current study reported lower accuracy rates, ranging from 60% to 63% for Decision Tree and Random Forest. Several reasons may account for these discrepancies. Firstly, variations in data pre-processing approaches, such as handling missing values through removal or imputation, could have influenced the results. Secondly, the current research utilized a nine-class activity prediction approach rather than binary classification, which may have contributed to the lower accuracy levels observed.

On the contrary, the extent to which the model might misclassify various activities performed by the elderly in a smart home environment is exposed. This misclassification can be attributed to the complexity and architecture of the machine learning models, which significantly impact the ability to accurately classify activities. While more advanced models tend to perform better, they can also be susceptible to overfitting when the training data is insufficient. Complicating matters further, certain home activities share similar sensors during the detection process, making it challenging for any model to distinguish between them accurately. For example, both *Meal_Preparation* and *Wash_Dishes* activities are detected using the same motion sensor, while *Leave_Home* and *Enter_Home* activities are associated with the same door sensor. Researchers and developers commonly employ various techniques to mitigate misclassifications, such as data augmentation, transfer learning, fine-tuning, or hyperparameter tuning, among others. These strategies help enhance the model's performance and reduce errors in classifying activities carried out by the elderly within a smart home environment.

A confusion matrix is a tabular representation that allows the evaluation of the performance of a classification model by comparing its predicted classes with the actual classes [25]. In the case of the Decision Tree model for activities k = 2, 3, 8, and 9 (*Eating, Housekeeping, Wash_Dishes*, and *Work*), the model failed to predict any of these activities, whether from the training or test datasets. On the other hand, the Random Forest model performed significantly better, even managing to predict some of the rare cases that the other two models struggled with. The Random Forest's superior performance is due to its nature as an ensemble learning method. Combining multiple Decision Trees allows the Random Forest algorithm to handle complex data relationships and interactions more effectively.

Additionally, it is less susceptible to overfitting compared to individual Decision Trees. This enhanced ability to capture nuances in the data makes it more adept at handling rare cases and improving true positive rates while reducing false negatives. Conversely, individual Decision Trees might suffer from overfitting and may not adequately capture intricate data patterns. Conclude that the Random Forest model's confusion matrix is expected to display higher true positive rates, fewer false negatives, and overall better performance on the specified activities due to its ability to combine multiple Decision Trees, effectively handling complex data relationships and rare cases.

Overall, the highest frequency of the activity recognized in the smart home environment is *Relax*. The drive to relax becomes more important as people age due to the physical, emotional, and social changes they experience [26]. Relaxation activities can improve well-being and a higher quality of life during aging. The ARUBA dataset suggests that increasing the frequency of relaxation activities could help normalize the situation, especially for older individuals who may require more time to unwind.

4. Conclusion

This research focused on three main aspects of human activity recognition, accuracy and robustness of the proposed machine learning models, and activity recognition prediction for the future. These aspects aim to assist in monitoring the health of elderly patients, enabling caregivers to be aware of their well-being. By monitoring changes in behaviour and health, patterns or trends can be identified earlier, leading to timely treatment or resolution of potential issues. The summary of this research contributes to the development of assistive technologies for monitoring the health and behaviour of elderly individuals, with the goal of timely intervention and improved care.

4.1 Recommendations and Implications

The recommendation to train and validate models that incorporate elderly people's health status and activity in smart homes is indeed valuable. Such models can help identify anomalies and monitor the condition of the elderly population, allowing caregivers and response teams to be more aware of their well-being.

Dementia, as mentioned, is a prevalent medical condition among the elderly, and it can profoundly impact their daily lives. By monitoring their activity patterns, smart home systems can detect deviations from their usual routines. For example, suppose an elderly person wakes up frequently at night due to an increased urge to use the restroom. In that case, the system can alert caregivers or adjust the lighting to make it easier and safer for them to navigate their way.

Memory loss is another significant symptom of dementia that can affect the elderly's well-being. Smart home systems can help address this issue by reminding individuals to perform essential tasks, such as eating meals or turning off appliances after use. The system can provide timely reminders or alerts to ensure their safety and prevent accidents or health problems by tracking their behaviour and identifying patterns.

Moreover, the ability of these models to recognize inappropriate behaviour or actions related to a specific medical condition can be extremely beneficial. For instance, if the system detects repetitive actions like leaving the stove on or failing to close water faucets, it can alert caregivers to prevent potential hazards, such as kitchen accidents or flooding. By identifying such patterns, caregivers can intervene and provide the necessary assistance or reminders to mitigate risks.

Additionally, the models can help identify sleepwalking or nocturnal activities that might pose a risk to the elderly. By analysing movement patterns during sleep or unusual activity during nighttime, caregivers can take appropriate measures to ensure their safety and well-being.

Future research could build upon these findings by exploring alternative machine-learning algorithms or improving the existing models. Additionally, investigating the integration of activity recognition with other healthcare monitoring systems could enhance the overall effectiveness of elderly care. Furthermore, applying these techniques in real-world scenarios, such as incorporating them into smart home technologies or wearable devices, holds promise for practical implementation.

In conclusion, integrating health status and activity monitoring into smart home systems can significantly improve the care and safety of the elderly, particularly those with dementia or other medical conditions. By training models to recognize abnormal behaviour patterns, caregivers can respond more effectively and provide appropriate care, enhancing the quality of life for the elderly population.

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