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Active LeZi:Spatio-Temporal Algorithm for Enhanced Senior In-Home Care System.

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ABSTRACT
With advances in technology and healthcare, the elderly population is increasing annually, making elderly care a significant challenge. To address this issue, countries worldwide are investing in long-term care centers and smart home facilities to mitigate the impact of an aged society, aiming to reduce labor resource depletion and alleviate the burden on caregivers. This study aims to alleviate the strain on nursing resources over the long term by leveraging smart home technology. However, effectively setting up a smart home environment remains a major issue. This study utilizes sensor data for statistical analysis and proposes improvements based on the Active LeZi algorithm. During the training process, 3 or 6 words encoding are read at a time to form phrases. Probabilities are assigned based on the proportion of character labels forming these phrases, which are then added to each label dictionary and incrementally encoded. After encoding, the phrase proportions within each dictionary are compared, and the label with the highest proportion is selected as the representative label for that phrase. This representative label is then added to the final dictionary. Confusion matrix analysis is performed on the test data based on the dictionary information, incorporating spatial division data to observe long-term living conditions and habits of the resident.The results indicate that 6 words encoding is optimal for activity labeling. This is because activity labeling data typically consists of continuous sequences of the same activity, and a larger window captures more information, enhancing prediction precision and recall. Conversely, 3 words encoding is more suitable for spatial division due to the variability in sequences triggered by activities.
By using this approach, this study aims to improve the accuracy and reliability of smart home systems, ultimately enhancing resident safety and reducing the burden on caregivers. The integration of sensor data analysis with refined encoding techniques offers a robust framework for monitoring and supporting elderly residents in a smart home environment.
KEYWORDS: Smart home, Active LeZi, Confusion matrix

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I. INTRODUCTION

According to the statistics from the National Development Council [1], Taiwan has transitioned into an aged society since 1993 and is expected to reach super-aged status by 2025. By 2070, it is projected that 4 out of 10 Taiwanese will be elderly, with 1 in 4 of them over 85 years old (Figure 1). This demographic shift is not unique to Taiwan but is a global concern. The implications of an aged society include increased economic burden on younger generations who often work away from home, leaving elderly individuals to live alone and necessitating costly nursing care services. Many families opt for nursing services, which can strain financial resources. Additionally, elderly individuals living alone face increased isolation and potential regret over their living arrangements. This study aims to alleviate the strain on nursing resources over the long term by leveraging smart home technology. While conventional smart home systems focus on convenience through sensor-equipped furniture and electronic devices, this study proposes a monitoring and nursing system. It utilizes sensor data for statistical analysis and employs machine learning algorithms to enable remote monitoring of elderly activities by caregivers.

The objective of this study is to develop a smart home system capable of behavior analysis. The system will capture activities such as sleep patterns, daily routines, and cooking, timestamping each event. Data will undergo analysis and machine learning processes to generate timelines and activity charts that track user habits and detect changes over time. These insights will be invaluable for medical professionals in assessing symptoms and monitoring disease progression.

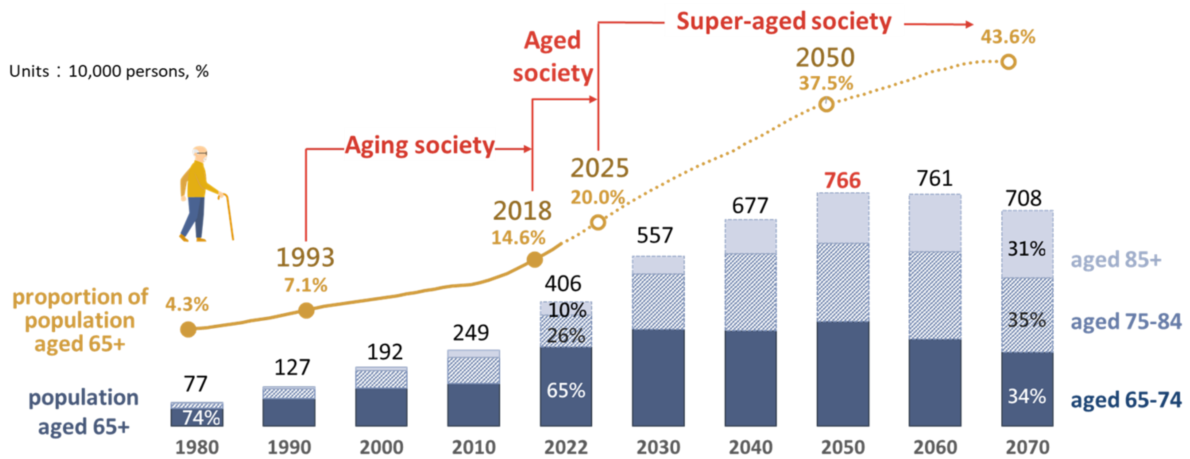

Figure 1 Elderly population in Taiwan. [1]

Continuous data collection from elderly residents is essential and must prioritize privacy. While options like webcams raise concerns due to their video and audio recording capabilities, sensors offer a more discreet choice for unobtrusive data collection. Sensors will gather time-series data on daily behaviors both indoors and outdoors, facilitating detailed analysis using activity recognition algorithms and machine learning models. These algorithms used for analyzing smart home data include Decision Tree, Support Vector Machine [2], Naive Bayes, Smart Home Inhabitant Prediction, Sequence Prediction Algorithms [3], LeZi 78 (LZ78), and Active LeZi (ALZ). However, these methods often involve complex mathematical computations and long processing times. There is still a significant gap before they can be practically applied in real-world environments.LZ78 [3-4], developed by Abraham Lempel and Jacob Ziv, is a foundational algorithm for lossless data compression. It operates by replacing longer phrases with tokens and decoding sequences through reverse search, ensuring efficient compression without data loss. ALZ [3, 5-7], introduced by Karthik Gopalratnam and Diane J. Cook in 2003, enhances LZ78 by improving sequence compression efficiency while preserving data integrity. This algorithmic approach is crucial in the context of smart home systems, where efficient data handling and storage are paramount.

The ALZ algorithm addresses the shortcomings of the LZ78 algorithm by using a sliding window approach to capture information lost at phrase boundaries. A dynamic window size is set based on the maximum character phrase length, retaining each item in the sequence. However, if the maximum length increases too slowly, the window retains many smaller, repetitive phrases, creating numerous new nodes in the Trie tree and complicating the problem. In practice, encoding with ALZ tends to slow down the growth of the Markov model hierarchy, especially with complex data, resulting in lower convergence speeds and repeated creation of short phrases, similar to LZ78, where short phrases have minimal utility. ALZ uses partial match prediction, which complements its difficulty in generating longer phrases by assigning higher weights to longer phrases while suppressing the reference value of shorter ones. This paper references ALZ's sliding window and partial match prediction concepts, modifying the window rules and applying frequency-based weighting for phrase occurrences and labels as the algorithm's foundation.

Activity recognition forms the backbone of smart home development. Each system component, from sensor placement influencing data quality to system architecture shaping data collection methods and noise reduction, plays a critical role. Effective algorithms for data processing are pivotal, as they determine the accuracy of activity identification and prediction. This study will integrate concepts from LZ78 and ALZ algorithms. Building on LZ78's sequence management, it will incorporate ALZ's sliding window technique to mitigate boundary information loss. This hybrid approach aims to develop novel algorithmic methods and integrate Sensor to Activity Mapping to optimize dictionary completeness for subsequent analysis.

II. MATERIAL AND METHOD

Based on the literature review of the LZ78 and ALZ algorithms, it's observed that LZ78 relies heavily on multi-character phrases during decoding, indicating that shorter phrases are of little use. This paper references LZ78's sequence data handling concepts and considers retaining the information encompassed within the data. By using ALZ's sliding window concept, encoded characters are rewritten repeatedly and incremented step-by-step, termed stepwise encoding. The window size is fixed to group phrases of 3 or 6 words. During continuous activities, the probability of multiple consecutive data points representing the same activity is lower than for three consecutive points, but the confidence in the phrase representing an activity is higher. Therefore, window sizes of 3 to 6 words are set for comparison and observation.

During transitions between activities, the triggered sensors vary, making the resulting phrases complex and unsuitable for direct activity identification. To address this, slight modifications are made during training. The phrase content is observed, and the activity label for each data point is recorded. If all labels are identical, the phrase's count in the respective activity dictionary is incremented by one. If multiple activity labels are present, the contribution of each activity within the phrase is calculated proportionally. For example (Figure 2), in three words encoding, if the phrase "M007 M007 M003" corresponds entirely to "Sleeping," it is incremented by one in the "Sleeping" dictionary. If the phrase "M007 M003 M004" has two points labeled "Sleeping" and one labeled "Bed_to_Toilet," it is incremented by 2/3 in the "Sleeping" dictionary and 1/3 in the "Bed_to_Toilet" dictionary. This method acknowledges the potential repetition of sequences in the same environment and assigns importance to frequently occurring phrases, thereby enhancing error tolerance and activity correlation.

```
2010-11-13 05:16:33.833857 M007 OFF Sleeping
2010-11-13 05:16:36.396413 M007 ON Sleeping
2010-11-13 05:16:37.811402 M003 OFF Sleeping
2010-11-13 05:17:05.045679 M004 OFF Bed_to_Toilet
2010-11-13 05:20:52.478511 M004 ON Bed_to_Toilet
2010-11-13 05:22:36.016359 M003 ON Sleeping
2010-11-13 05:22:38.078034 M002 OFF Sleeping
2010-11-13 05:22:39.941485 M003 OFF Sleeping
```

Figure 2 Example of Activity Interval Data.

Each phrase's occurrence is recorded for each activity. The total occurrences of all phrases in an activity dictionary are summed to calculate each phrase's percentage. Higher occurrences indicate greater importance for that activity. Given that a phrase can appear in multiple activity dictionaries, its relative importance is calculated by comparing its proportions across all dictionaries, selecting the highest proportion as the representative activity. For example, if the phrase "M007 M003 M004" appears in both "Sleeping" and "Bed_to_Toilet" dictionaries, the respective counts and proportions are compared to determine its primary activity, which is then added to the final dictionary. After completing 3 to 6 words encoding, dictionaries representing each activity are established. Phrases' probabilities within each activity are converted into proportions, and the highest proportion for each phrase is added to the final dictionary. The activity labels are removed, and the test data sequences are stepwise encoded. Phrases are searched in the dictionary to determine corresponding activities, which are then compared with original labels for confusion matrix analysis. This analysis helps observe residents' living conditions and evaluate sensor setup effectiveness.

Although the confusion matrix helps observe residents' living conditions and changes, it can be challenging to understand the actual living conditions in detail. Therefore, we use data to create resident activity label analysis charts presented in two dimensions, allowing intuitive observation of resident’s daily condition. This provides useful detailed information for caregivers with minimal data. Confusion matrix analysis reveals the relationships between activities and evaluates the overall sensor setup in a smart home environment. By observing long-term living conditions through the confusion matrix and short-term habits through analysis charts, the cross-referenced results enhance analysis credibility and provide comprehensive insights into resident’s activities.

Experimental dataset

The CASAS (Center for Advanced Studies in Adaptive Systems) dataset was utilized in this study [8]. CASAS is an open-source database designed for testing and collecting real data through a smart home environment situated at Washington State University's Pullman campus. We selected a specific dataset named Aruba. Sensors embedded in the smart home generate readings as residents go about their daily routines. Figure 3 illustrates an example of activity events in a smart home. We divided the Aruba dataset into training and testing sets. Each instance in the training set includes a target value (i.e., the class labels). Sensors are strategically deployed in the smart home to gather information about the resident's daily activities.

Infrared sensors, denoted as "M", record the trajectory of the inhabitant when crossed, providing data crucial for identifying activities. Door sensors, denoted as "D", are installed on doorknobs to determine if the inhabitant is entering or leaving a room, thus helping the system identify the inhabitant's movement within the space. Thermal sensors, denoted as "T", regularly measure temperature. However, to simplify the process and algorithm, thermal sensors will not be used in this study for analysis. Numerous sensors are present in the living environment, each marked with a specific type and number. The environmental setup can be referred to in Figure 4, which aids in observing and analyzing user behavior more effectively.

Date	Time	Sensor	State	Activity labeled
2010-11-04	11:41:32.570925	M022	OFF	
2010-11-04	11:41:34.029848	D004	OPEN	Leave_Home begin
2010-11-04	11:41:37.192624	M030	ON	
2010-11-04	11:41:43.345957	D004	CLOSE	Leave_Home end
2010-11-04	11:41:44.121	M030	OFF	
2010-11-04	11:43:30.094537	D004	OPEN	Enter_Home begin
2010-11-04	11:43:30.658939	M030	ON	
2010-11-04	11:43:34.541657	M030	OFF	
2010-11-04	11:43:34.683398	D004	CLOSE	Enter_Home end
2010-11-04	11:43:35.454279	M022	ON	

Figure 3 Format of CASAS Aruba Database [8]

In this study, spatial division is used for analysis based on the premise that the actual regions traversed by residents during activities do not change. Even if there are slight errors in activity label records or ambiguities at the boundaries between activities, spatial division analysis can cross-reference the results with activity label analysis, enhancing the credibility and yielding results closer to reality. Activity tags classify and elucidate residents' daily activities. Combining these tags with spatial division analysis provides deeper insights into the areas where residents spend most of their time. Cross-comparing the results of activity tag analysis with spatial data allows us to verify the correlation between activities and spaces, thus increasing the credibility of the experimental analysis.

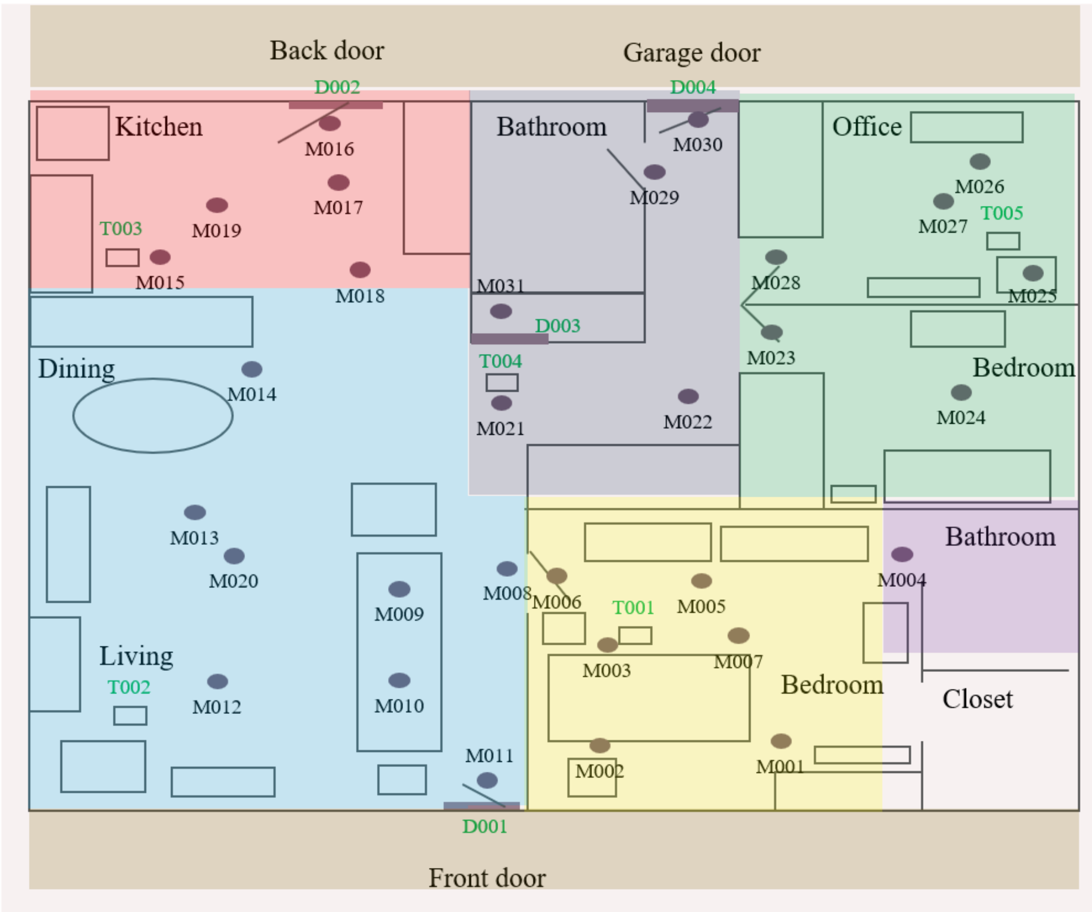

Figure 4 Sensors setting in smart home environment

To correspond to the 11 types of activities in the dataset, activities occurring in the same area are grouped into the same spatial division. Based on Table 1, the sensor distribution can be divided into seven spaces, as illustrated in Figure 4. This approach allows for more reliable and accurate analysis by aligning spatial data with activity labels. The user activities are categorized into 11 activity labels: "Sleeping", "Bed_to_Toilet", "Meal_Preparation", "Relax", "Housekeeping", "Eating", "Wash_Dishes", "Leave_Home", "Enter_Home", "Work" and "Respirate". The sensors, activity labels and spaces are categorized in Table 1, organized by the number of sensors.

Table 1 Mapping between spaces and sensors

Space (Activity Label)	Sensor number
Bedroom (Sleeping)	M001 M002 M003 M005 M006 M007
Bathroom (Bed_to_Toilet)	M004
Living (Relax & Eating)	M008 M009 M010 M011 M012 M013 M014 M020
Kitchen (Wash_Dishes&Meal_Preparation)	M015 M016 M017 M018 M019
Office (Work & Respirate)	M023 M024 M025 M026 M027 M028
Other (Housekeeping)	M021 M022 M029 M031 D003
Outside (Leave & Enter home)	D001 D002 D004 M030

Software Implementation

The software includes a training mode and a testing mode. The following sections will introduce their architecture and flowchart sequentially. In training mode, the process begins by reading the training data. The sensor numbers and activity labels from the data are separated into different lists. The user then selects either 3 words encoding or 6 words encoding. Based on the selected encoding method, the sensor numbers are read in groups of three or six to form word groups, as illustrated in Figure 5.

For each word group, the proportion of each character's corresponding label is calculated. The system checks if this word group exists in the label dictionary. If it does not, the word group and its corresponding proportions are added to the dictionary. If it does exist, the proportions are updated by accumulation. After processing the current word group, the first data entry is deleted, and it is checked whether the training data is exhausted. If data remains, the above steps are repeated. If no data remains, the proportion of each word group within each label dictionary is calculated. The word group is then assigned the label with the highest proportion, designating it as the representative activity for that word group. This word group and its representative label are added to the final dictionary, concluding the training process. The flowchart for the training mode is illustrated in Figure 6.

```
1  2010-12-08 16:35:48.39284 M013 ON Relax
2  2010-12-08 16:35:51.699143 M020 OFF Relax
3  2010-12-08 16:35:52.755055 M009 OFF Relax
4  2010-12-08 16:50:08.451455 M026 ON Work
5  2010-12-08 16:50:10.975658 M026 OFF Work
6  2010-12-08 16:50:24.346274 M026 ON Work
7  2010-12-08 16:50:32.164207 M026 OFF Work
8  2010-12-08 16:50:56.764056 M026 ON Work
9  2010-12-08 16:51:02.082993 M026 OFF Work
10 2010-12-08 16:51:19.682573 M026 ON Work
```


Figure 5 Example of 3 words encoding.

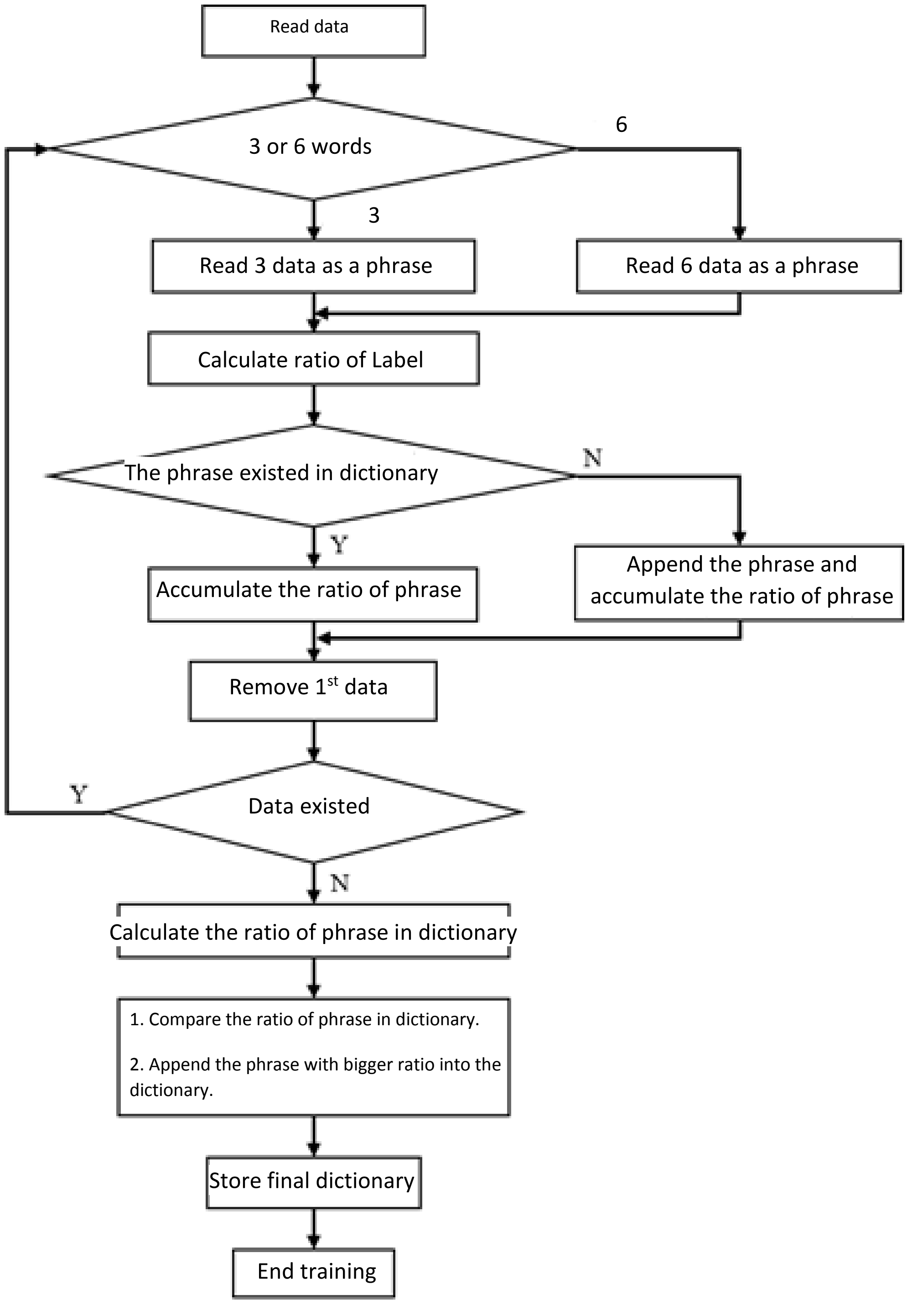

Figure 6 Flowchart of the training mode.

In testing mode, the process begins by reading the test data, separating sensor numbers and activity (space) labels into different lists. Then, it reads the pre-trained dictionary (3 words or 6 words). Based on the dictionary's encoding, it determines whether to use 3 words or 6 words to form word groups from the test data. These word groups are used to search for corresponding entries in the dictionary. If a word group is not found, the number of occurrences of unfound word groups is recorded. If found, the label of the first character of the word group and the associated representative activity from the dictionary are recorded. Next, a confusion matrix judgment (TP, TN, FP, FN) is performed using these labels, and the results are stored in the label-specific confusion matrix dictionary. The first data entry is then deleted, and it is checked whether the test data is exhausted. If data remains, the above steps are repeated. If no data remains, the confusion matrix dictionary for each label is extracted, and the Accuracy, Precision, and Recall are calculated. The TP and FN for each label are displayed, concluding the test. The flow of the testing mode is shown in Figure 7.

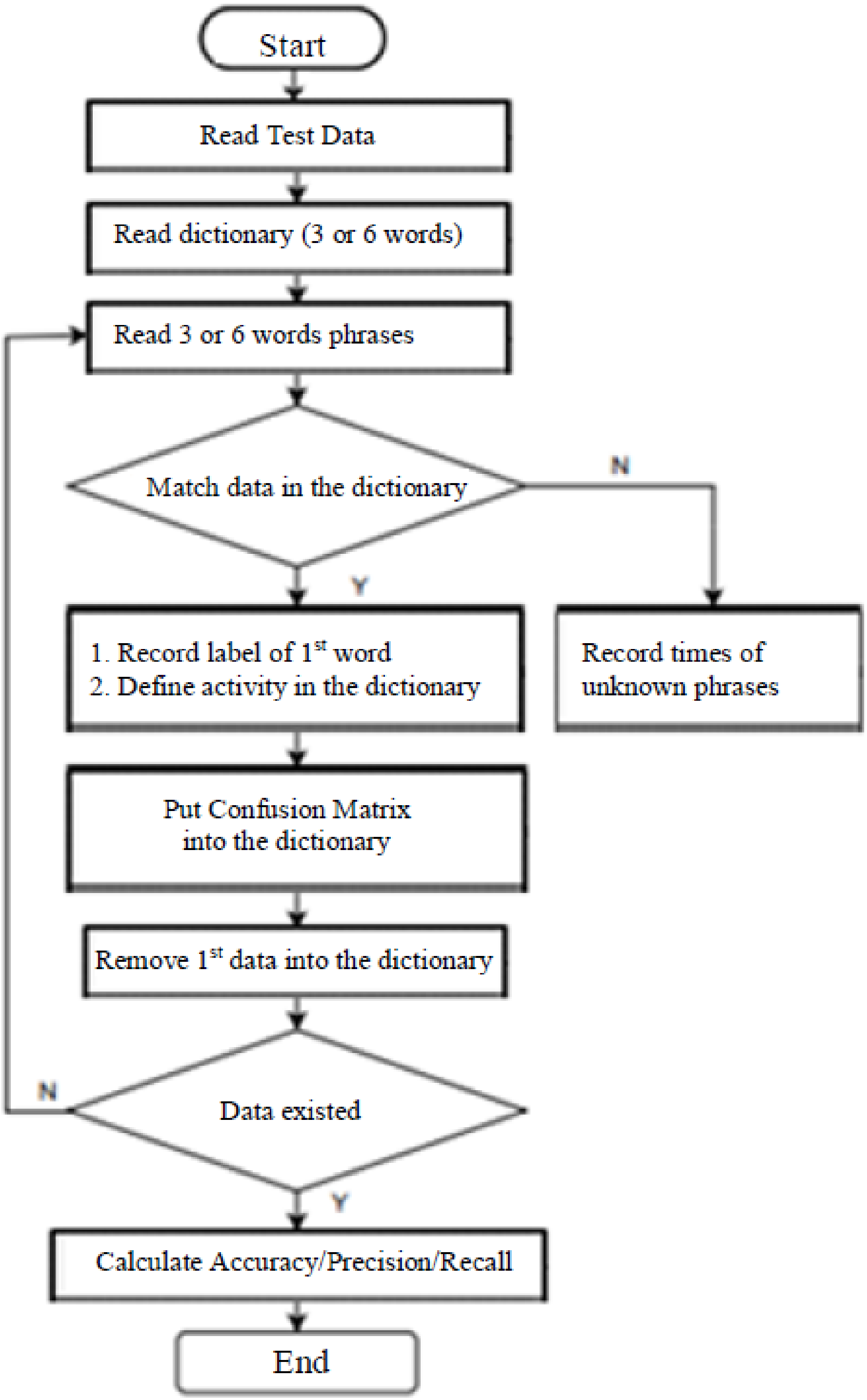

Figure 7 Flowchart of the testing mode.

III. RESULT AND DISCUSSION

To understand the information provided by the data, we use the precision of the confusion matrix to observe whether the prediction accuracy for a particular activity is reliable. Recall is used to determine the impact of predictions for one activity on the prediction of other activities across the entire dataset. The experiment is designed to analyze 100,000 data entries individually. The window size is set to observe 3 words and 6 words encodings. After analyzing 100,000 data entries, the model is trained to obtain the final dictionary set. The performance of predictions for each activity under different encodings is then evaluated.

Confusion matrix analysis of activity classification

Precision and recall are calculated as shown in Table 2 and 3. In these tables, blue text represents True Positive (TP), horizontal black text represents False Positive (FP), and vertical black text represents False Negative (FN). This table allows us to see which activities the model most frequently mis-predicts and the frequency of these errors. By analyzing this, we can understand which activities are most likely to be confused with each other, indicating the highest correlation of mutual influence. Precision helps us evaluate the performance of predictions for a specific activity, while Recall shows the proportion of impact on the prediction of other activities.

Table 2 Confusion matrix of activity classification by using 3 words encoding (trained 100,000 / tested 100,000).

Prediction \ Real	Sleeping	Bed_to_Toilet	Meal_Preparation	Relax	Housekeeping	Eating	Wash_Dishes	Leave_Home	Enter_Home	Work	Respirate	Precision
Sleeping	8958	125			219	1	2	24	4	2		95.96%
Bed_to_Toilet		426			16							96.38%
Meal_Preparation	56	10	18701	167	899	111	10115	67	61	8	6	59.94%
Relax	399	4	119	34787	1605	140	31	50	2	134	15	93.30%
Housekeeping	2559	403	334	642	4771	584	256	99	29	66	61	63.58%
Eating	18	1	108	36	133	4087	77	28	3	4		90.92%
Wash_Dishes	16		1686	7	86	130	1820	22	12	9	7	47.96%
Leave_Home			2		2			333	152	1	2	67.68%
Enter_Home			1		1			151	377			71.13%
Work	41	1		4	28	6	5	18	3	4044	564	85.79%
Respirate										34	170	83.33%
Recall	91.91%	43.92%	89.26%	97.60%	61.48%	67.45%	14.79%	42.05%	58.63%	94.00%	20.61%	Acc : 78.47%

Table 3 Confusion matrix of activity classification by using 6 words encoding (trained 100,000 / tested 100,000).

Prediction \ Real	Sleeping	Bed_to_Toilet	Meal_Preparation	Relax	Housekeeping	Eating	Wash_Dishes	Leave_Home	Enter_Home	Work	Respirate	Precision
Sleeping	8984	244	38	2	62			5				96.24%
Bed_to_Toilet		442										100.00%
Meal_Preparation	11	3	21570	160	472	745	8190	24	1	19	6	69.13%
Relax	352	1	227	35822	546	78	19	120		110	8	96.08%
Housekeeping	159	137	106	306	6353	210	118	51	1	47	16	84.66%
Eating	5		5	13	22	4294	90	56		10		95.53%
Wash_Dishes	1		736	14	7	50	2973	8		6		78.34%
Leave_Home								301	191			61.18%
Enter_Home						1		158	361	10		68.11%
Work	19			2	10	6		19	1	4384	273	93.00%
Respirate										10	194	95.10%
Recall	94.26%	53.45%	95.10%	98.63%	85.02%	79.75%	26.10%	40.57%	65.05%	95.39%	39.03%	Acc : 85.68%

From Table 2, it is evident that the Precision for the activity "Meal_Preparation" is only 59.94%. This is primarily due to the high number of instances where it is misclassified as the activity "Wash_Dishes," occurring 10,115 times. Both activities take place in the kitchen, overlapping in the same area and triggering mostly the same sensors. For a sequence prediction algorithm, the high overlap in word groups makes it difficult to accurately distinguish between the two activities, indicating a significant mutual influence. This demonstrates that using only infrared motion sensors is insufficient for accurately determining resident's behavior. Adding sensors on the stove and refrigerator would increase the uniqueness of the word groups for "Meal_Preparation," effectively reducing the likelihood of it being misclassified as "Wash_Dishes." The activities "Leave_Home" and "Enter_Home" have lower Precision due to the lack of detectable sensors once the resident leaves the home, resulting in fewer word groups and a lack of diversity, which impacts the accuracy of predicting entry and exit activities. Upon entering the home, other sensors are continuously triggered, allowing the formation of new word groups, hence the higher prediction accuracy for entry compared to exit. Using the same training and testing dataset sizes, we observed the confusion matrix with 6 words encoding, as shown in Table 3. Precision for each activity improved, as longer sequences of sensor activations during continuous resident activities increase the likelihood of obtaining consistent activity labels. This highlights the discriminative power of word groups for activity labels, and the probabilistic assignmentmethod mentioned in the study shows significant improvements in Precision and Recall with 6 words encoding.

Compare Table 2 and Table 3, the Precision for "Meal_Preparation" increased to 69.13%. While this Precision is still not ideal, the 9.14% improvement with 6 words encoding indicates that despite both activities occurring in the same area, 6 words encoding can effectively distinguish between them. Adding critical sensors can further establish unique word groups for each activity, potentially enhancing performance with 6 words encoding. Similarly, the activities "Leave_Home" and "Enter_Home" benefit from 6 words encoding, as it increases the connection to subsequent sensor activations, improving prediction Precision. Installing sensors on door handles or at the entrance can establish specific sequential word groups for entering and leaving, differentiating whether the resident is coming or going rather than just detecting door movement. Strategic placement of meaningful sensors maximizes efficiency.

From the Recall perspective, Table 3 shows that the activity "Wash_Dishes" has a Recall of only 26.10%, indicating a significant impact on the prediction of other activities. Most notably, the FN for "Wash_Dishes" affects "Meal_Preparation" (8,190 times). This analysis demonstrates the relationship between activities through Precision and Recall, validating the confusion matrix as a reliable model evaluation metric. Under the same training and testing conditions, hexa-gram encoding achieved an Accuracy of 85.68%, a 7.21% improvement over tri-gram encoding. This confirms that longer word groups lead to higher prediction accuracy in continuous activities.

Confusion matrix analysis of spatial division

Using activity labels to categorize can help us understand resident's daily activities. If we further analyze this data with spatial divisions, we can better understand where resident spends most of their time and cross-reference this with activity label analysis results. By examining the correlation between activities and spaces, we can determine if they align with actual behavior, enhancing the credibility of the experimental analysis. For the experiment based on spatial division, the same standards as the activity label experiment were applied, analyzing 100,000 data entries using 3 words and 6 words encoding. As shown in Table 4, it was found that the precision of the spatially divided experiment was generally better than that of the activity-based categorization. This is primarily because there is no need to distinguish between activities in the same area, such as "Meal_Preparation" and "Wash_Dishes" in the "Kitchen." The precision difference between these activities under 3 words encoding, as shown in Table 2, confirms that the two activities influence each other and cannot be clearly distinguished due to the lack of unique phrases. To accurately identity behavioral activities, the sensors must be installed in the right place.

Table 4 Confusion matrix of the spatial division by using 3 and 6 words encoding. (trained 100,000/tested 100,000)

Original			Real							
3 words			Bedroom	Bathroom	Kitchen	Living	Other	Outside	Office	Precision
Trained data: 100,000	Prediction	Bedroom	3772	170			28	2	9	94.75%
Tested data: 100,000		Bathroom		143						100.00%
Duration: 7.01s		Kitchen	3		34279	663	659	31	1751	91.69%
Accuracy: 89.72%		Living	164	8	1060	42940	574	75	1643	91.69%
		Other					1461	109		93.06%
		Outside						352		100.00%
		Office	9	8			510	11	6774	92.64
		Recall	95.54%	43.47%	97.00%	98.48%	45.20%	60.69%	66.56%	
6 words			Bedroom	Bathroom	Kitchen	Living	Other	Outside	Office	Precision
Trained data: 100,000		Bedroom	3191	201	7	8	6	2	9	93.20%
Tested data: 100,000		Bathroom		106						100.00%
Duration: 7.01s		Kitchen			27827	315	150	8	545	96.47%
Accuracy: 72.95%		Living	83	6	479	36799	86	98	1734	93.67%
		Other	1	1			146	45	40	62.66%
		Outside						156		100.00%
		Office	5	3	66	22	34	1	4727	97.30%
		Recall	97.29%	33.44%	98.05%	99.07%	34.60%	50.32%	67.00%	

Observing the Recall values, the three lowest areas are "Bathroom", "Other" and "Outside". The activity "Bed_to_Toilet" in the "Bathroom" shows a similar situation in the activity label analysis. There are six sensors in the "Bedroom" and during the transition from the bed to the toilet, sensors along the way and in the bathroom form a phrase, leading to excessive "Bedroom" false negative (FN) in the "Bathroom." The "Other" area, being a node connecting various spaces, easily influences the prediction of other spaces, particularly "Kitchen" and "Living", which have the highest times. Thus, a low Recall value for "Other" is understandable. The poor precision of "Other" is also due to its position as a connecting node and an area frequently traversed by various activities, making it with the most mixed data and the most diverse phrases. Increasing the variety of sensors could establish unique phrases for each space, leading to more effective and accurate classification.

From Table 4, it is observed that 3 words encoding has better accuracy than 6 words encoding, contrary to the trend in activity classification analysis. The reason lies in the sequence of labels in the data. Activity labels consist of continuous segments of the same activity, allowing 6 words encoding to accurately match phrases to activity labels. In spatial division, due to different sensor locations, the data sequence becomes more mixed. The 6 words encoding struggles to balance the information within phrases to represent the correct space, whereas 3 words encoding, capturing less information, identifies spaces more accurately under spatial division.

Using spatial division yields better accuracy compared to activity labeling, with 3 words encoding achieving around 90% accuracy. This validates that spatial division is more suitable for 3 words encoding, as it is robust to sequence noise, while activity labeling is more suited to 6 words encoding, which is better for predicting continuous label sequences.

To further understand the correlation between the activities and the spaces, Figure 8 presents a daily activity report. The X-axis represents time (24-hour format), and the Y-axis unfolds activity classification data and spatial division data over time. From Figure 8, it is observed that the spatial divisions "Bedroom" and "Bathroom" and the activity classifications "Sleeping" and "Bed_to_Toilet" share the same trend. Around 8:00, the spatial division analysis graph shows overlapping colors, making it difficult to distinguish between areas. Correspondingly, the activity classification graph shows that the resident is performing "Meal_Preparation" indicating movement to the "Kitchen" to prepare a meal. During this time, the resident passed through various spaces from "Bedroom" to "Kitchen", and the changes will be reasonable.

From 8:00 to 11:00, the activity labels indicate "Work" and "Housekeeping", the spatial division analysis still shows movement through various spaces. The "Work" activity indicates that the resident moves between various corresponding spaces, whereas the "Housekeeping" activity involves traversing and cleaning across all areas, inevitably triggering sensors throughout the house. Around 11:00 to 13:00, after the resident goes out and returns, the activity labels align with the spatial division analysis. From the above analysis and discussion, it is evident that activity classification analysis can clearly understand the resident's activity goals, while spatial division analysis can determine the spaces used during these activities. For example, contrasting "Work" with spatial changes demonstrates that simply identifying the "Work" activity does not provide insight into the resident's working conditions. However, the spatial division graph reveals the resident's activity patterns. Both activity and spatial analyses are effective in understanding the resident's lifestyle. In the future, when long-term care personnel need to assess resident's living conditions, this analytical data can offer valuable insights, improving caregiver's understanding of the resident and maximizing the benefits of care.

Figure 8 Daily report of activity classification and spatial division.

IV. CONCLUSION

Confusion matrix analysis indicates that 6 words encoding is optimal for activity labeling. This is because activity labeling data typically consists of continuous sequences of the same activity, and a larger window captures more information, enhancing prediction precision and recall. In contrast, 3 words encoding is more suitable for spatial division due to the variability in sequences triggered by activities. Given the complexity of activity labels, 3 words encoding provides superior noise resistance and predictive performance. Additionally, confusion matrix analysis can elucidate resident's living habits and assess the effectiveness of sensor placement. The spatial analysis method is similar to semi-supervised learning, which reduces the risk of human error or incorrect recording and supports the validity of activity label analysis. In the future, spatial division could be directly applied to smart home care and analysis, reducing labor costs and simplifying implementation.

A two-dimensional analysis chart can simultaneously display a resident's daily activities, offering a clear and intuitive understanding of their status for caregivers, thereby reducing their workload. Future advancements could include real-time systems that evaluate and reduce the risk of accidents based on analytical results. Experimental outcomes from spatial analysis validate this classification method's reliability. Implementing this concept in a smart home environment can significantly enhance resident safety.

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