

Machine Learning Techniques to Classify Individual's Home Activities

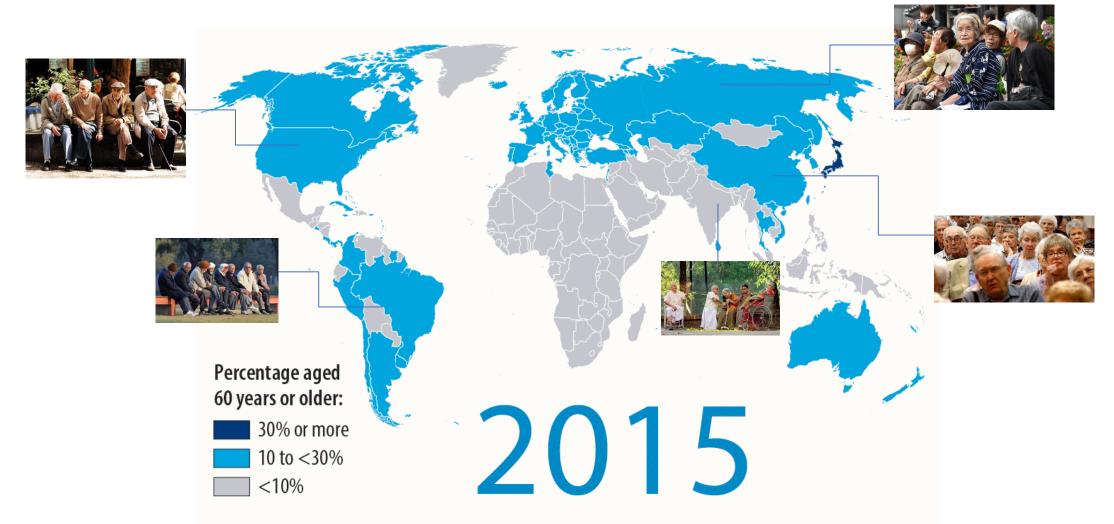
Presented by Ms Chong Kar Yin, Taylor's University





AGING POPULATION: THE CHALLENGE

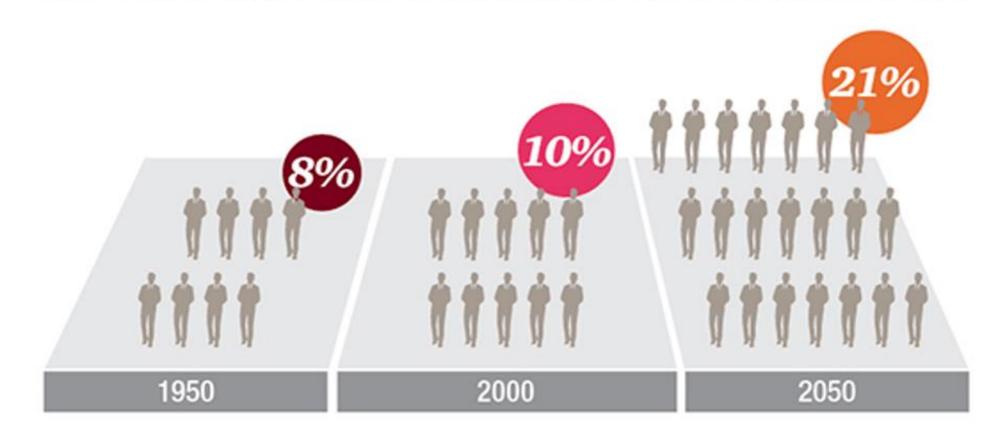
THE POPULATION IS GETTING OLDER



Source: World Health Organization

THE POPULATION IS GETTING OLDER

Proportion of the world population aged 60 years or more



Source: UN Report World Population Ageing 1950-2050



24-Hour **Caregivers?**

11Th MALAYSIA STATISTICS CONFERENCE

9612



Healthcare **Investment?**

11Th MALAYSIA STATISTICS CONFERENCE







More Subsidy?

11Th MALAYSIA STATISTICS CONFERENCE







11Th MALAYSIA STATISTICS CONFERENCE

OUR STUDY

11Th MALAYSIA STATISTICS CONFERENCE

METHODOLOGY ALGORITHM PERFORMANCE **FUTURE WORK OBJECTIVE FINDINGS**

01

Compare machine learning algorithms for classifying ADLs using smart home data.



Assess the impact of time-related features on classification accuracy.



11Th MALAYSIA STATISTICS CONFERENCE

METHODOLOGY ALGORITHM PERFORMANCE **OBJECTIVE FUTURE WORK** FINDINGS



Compare machine learning algorithms for classifying ADLs using smart home data.



Assess the impact of timerelated features on classification accuracy.



11Th MALAYSIA STATISTICS CONFERENCE

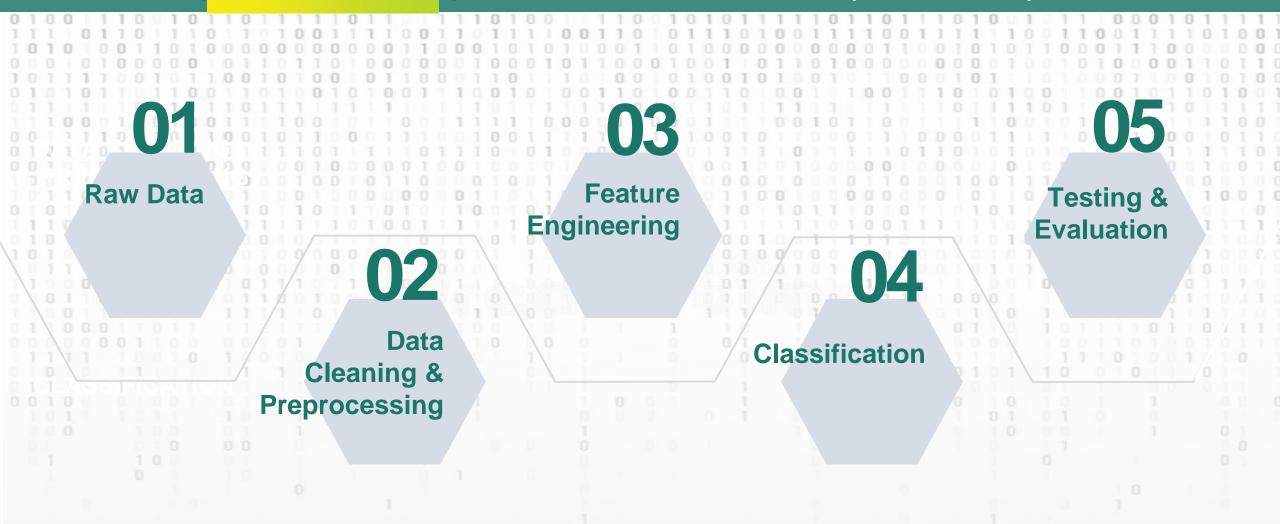
OBJECTIVE

METHODOLOGY

ALGORITHM PERFORMANCE

FINDINGS

FUTURE WORK



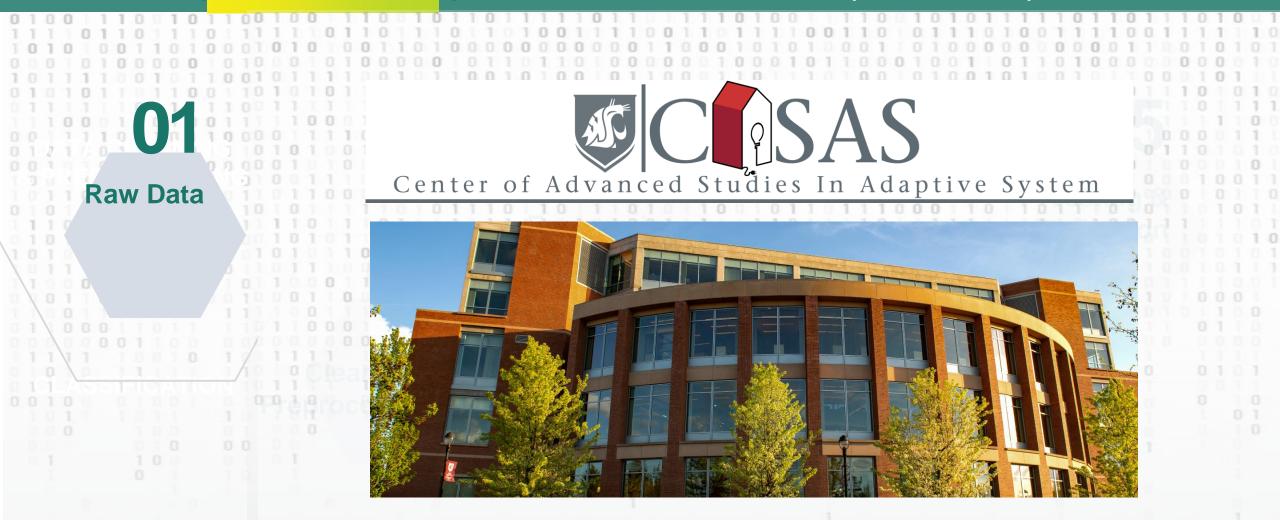
11th MALAYSIA STATISTICS CONFERENCE



ALGORITHM PERFORMANCE

FINDINGS

FUTURE WORK



OBJECTIVE

Data

Cleaning &

Preprocessing

METHODOLOGY

ALGORITHM PERFORMANCE

Garage Door

Office

M027

M024

M004

M007

M001

Bedroom

Bedroom

Bathroom

Closet

M026

T005

M025

D004

M028

M023

M005

Front Door

FINDINGS

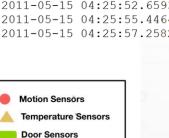
FUTURE WORK



Back Door

Date	Time	Sensor	Status Annotation
2011-05-15	04:22:43.082116	M003	ON
2011-05-15	04:22:44.624551	M003	OFF Sleeping e
2011-05-15	04:22:46.649038	M005	ON
2011-05-15	04:22:50.398987	M004	ON Bed to Toi
2011-05-15	04:22:50.472761	M005	OFF
2011-05-15	04:22:57.782528	T005	21
2011-05-15	04:22:58.533178	M004	OFF
2011-05-15	04:22:58.623508	M007	OFF
2011-05-15	04:25:44.619463	M004	ON
2011-05-15	04:25:45.993194	M007	ON
2011-05-15	04:25:50.590135	M004	OFF Bed to Toi
2011-05-15	04:25:50.727788	M005	ON
2011-05-15	04:25:52.659384	M005	OFF
2011-05-15	04:25:55.446432	M003	ON Sleeping b
2011-05-15	04:25:57.258257	M007	OFF

D002 Bathroom M030 M016 **Kitchen** M017 M029 M015 M019 T003 M018 M031 T004 M014 M022 M021 Dining M013 M006 M008 M009 M020 TOO Living M003 T002 M012 M010 M002 M011



Ignored Door Sensors

OFF	Sleeping end
ON	
ON	Bed to Toilet begin
OFF	
21	
OFF	
OFF	
ON	
ON	
OFF	Bed to Toilet end
ON	
OFF	
ON	Sleeping begin
OFF	

11th MALAYSIA STATISTICS CONFERENCE "Data and Artificial Intelligence: Empowering the Future"

D001

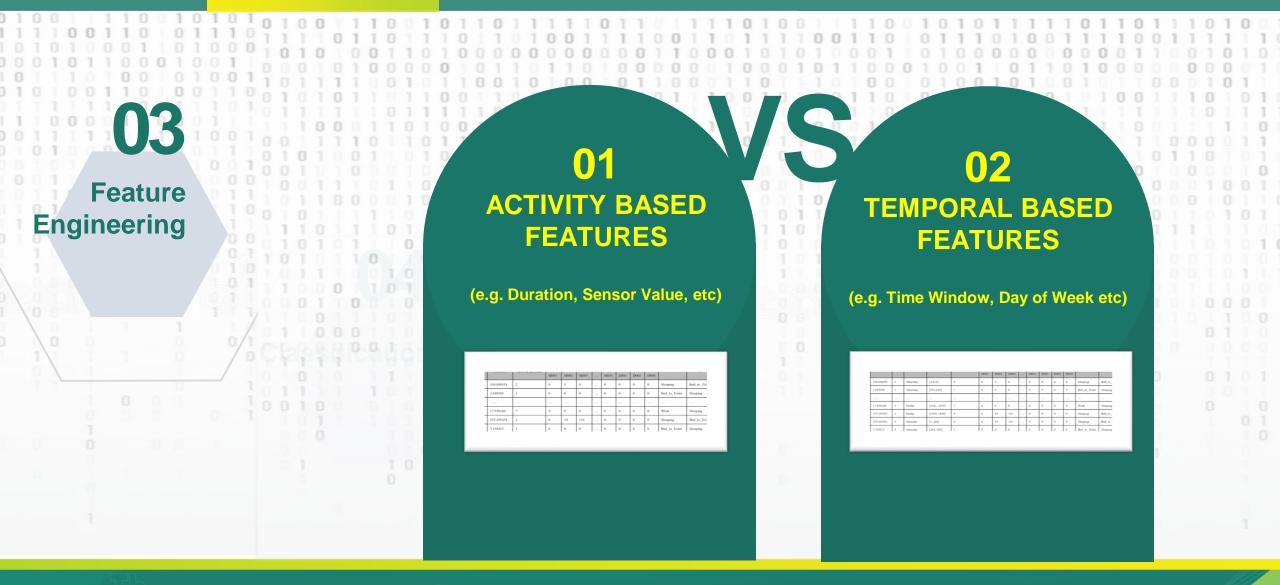
OBJECTIVE

METHODOLOGY

ALGORITHM PERFORMANCE

FINDINGS

FUTURE WORK

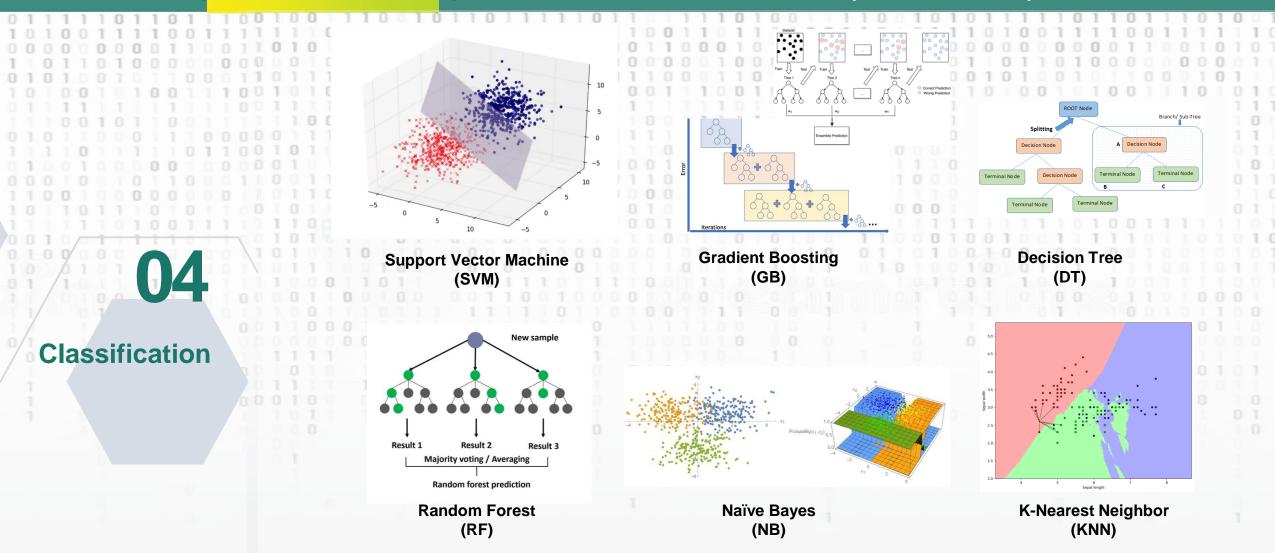


OBJECTIVE METHODOLOGY

ALGORITHM PERFORMANCE

| FINDINGS

FUTURE WORK



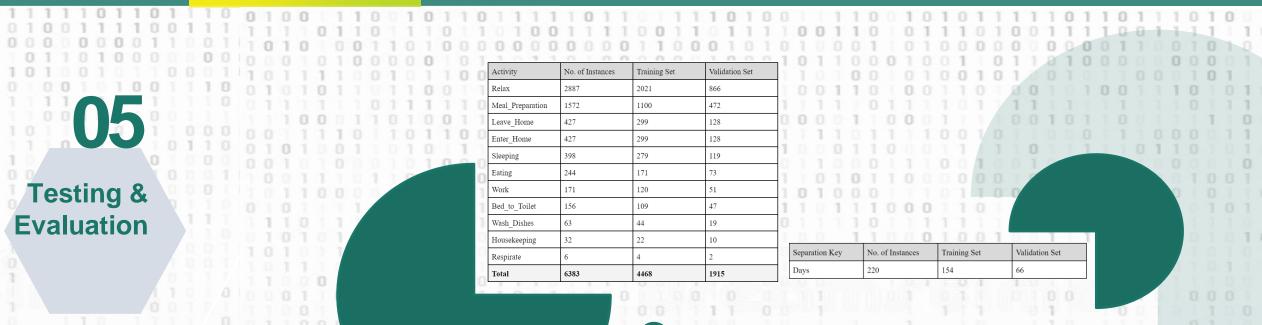
OBJECTIVE

METHODOLOGY

ALGORITHM PERFORMANCE

FINDINGS

FUTURE WORK





Cross Validation Test

Evaluation Metrics

- Confusion Matrix
- Precision | Recall
- F1 Score
- Matthews Correlation Coefficient

11Th MALAYSIA STATISTICS CONFERENCE

01

Compare machine learning algorithms for classifying ADLs using smart home data.



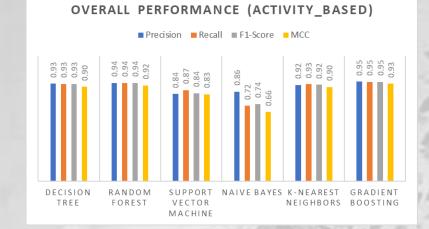
Assess the impact of time-related features on classification accuracy.

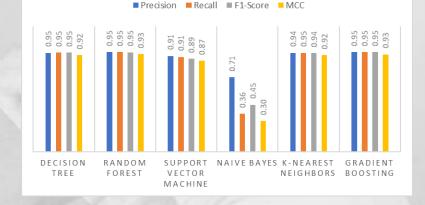


11Th MALAYSIA STATISTICS CONFERENCE

01 Comparing Algorithms

- Gradient Boosting: Top performing algorithm
- Random Forest & Decision Trees:
 Strong performance on complex activities
- Naive Bayes: Worst performance, struggled with interdependent data





OVERALL PERFORMANCE (DAILY_BASIS)

11Th MALAYSIA STATISTICS CONFERENCE



Compare machine learning algorithms for classifying ADLs using smart home data.



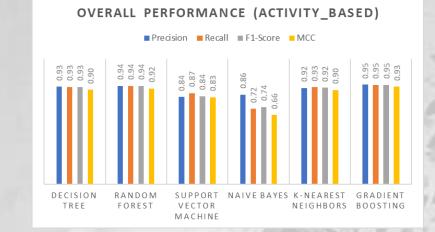
Assess the impact of timerelated features on classification accuracy.

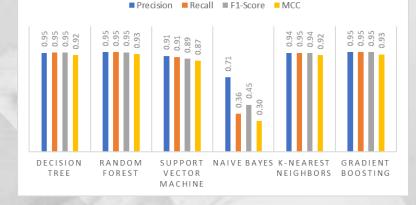


11Th MALAYSIA STATISTICS CONFERENCE

02 Impact of Time Features

- Improved accuracy in most models
- SVM showed the biggest improvement
- Random Forest slightly outperformed Gradient Boosting with time features





11Th MALAYSIA STATISTICS CONFERENCE

"Data and Artificial Intelligence: Empowering the Future"

OVERALL PERFORMANCE (DAILY_BASIS)

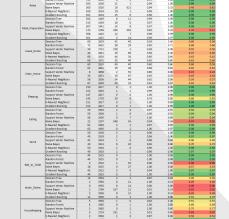
RESULT DETAILS

Activity	Method	TP	TN	FP	FN	Precision	Recall	F1-Score	MCC
	Decision Tree	869	1035	9	2	0.99	1.00	0.99	0.9
	Random Forest	870	1040	- 4	1	1.00	1.00	1.00	0.9
Relax	Support Vector Machine	869	1030	14	2	0.98	1.00	0.99	0.9
Relax	Naive Bayes	758	1040	4	113	0.99	0.87	0.93	0.0
	K-Nearest Neighbors	868	1037	7	3	0.99	1.00	0.99	0.
	Gradient Boosting	870	1044	0	1	1.00	1.00	1.00	
	Decision Tree	429	1468	6	12	0.99	0.97	0.98	0.
	Random Forest	437	1466	8	- 4	0.98	0.99	0.99	0.
Meal Preparation	Support Vector Machine	434	1452	22	7	0.95	0.98	0.97	0.
weat_preparation	Naive Bayes	167	1461	13	274	0.93	0.38	0.54	0.
	K-Nearest Neighbors	437	1452	22	4	0.95	0.99	0.97	0.
	Gradient Boosting	435	1467	7	6	0.98	0.99	0.99	0.
	Decision Tree	78	1729	71	37	0.52	0.68	0.59	0.
	Random Forest	71	1746	54	44	0.57	0.62	0.59	0.
Leave Home	Support Vector Machine	115	1593	207	0	0.36	1.00	0.53	0.
Leave_nome	Naive Bayes	1	1797	3	114	0.25	0.01	0.02	0.
	K-Nearest Neighbors	81	1731	69	34	0.54	0.70	0.61	0.
	Gradient Boosting	86	1749	51	29	0.63	0.75	0.68	0.
	Decision Tree	68	1742	36	69	0.65	0.50	0.56	0.
	Random Forest	83	1734	44	54	0.65	0.61	0.63	0.
	Support Vector Machine	0	1778	0	137	0.00	0.00	0.00	0.0
Enter_Home	Naive Bayes	132	1666	112	5	0.54	0.96	0.69	0.1
	K-Nearest Neighbors	70	1744	34	67	0.67	0.51	0.58	0.
	Gradient Boosting	88	1750	28	49	0.76	0.64	0.70	0.
	Decision Tree	139	1774	1	1	0.99	0.99	0.99	0.9
	Random Forest	139	1775	0	1	1.00	0.99	1.00	1.
	Support Vector Machine	130	1775	0	10	1.00	0.93	0.96	0.
Sleeping	Naive Bayes	139	1773	2	1	0.99	0.99	0.99	0.
	K-Nearest Neighbors	137	1775	0	3	1.00	0.98	0.99	0.9
	Gradient Boosting	140	1775	0	0	1.00	1.00	1.00	1.
	Decision Tree	77	1835	1	2	0.99	0.97	0.98	0.9
	Random Forest	77	1834	2	2	0.97	0.97	0.97	0.
	Support Vector Machine	71	1836	0	8	1.00	0.90	0.95	0.
Eating	Naive Bayes	74	1573	263	5	0.22	0.94	0.36	0.4
	K-Nearest Neighbors	78	1835	1	1	0.99	0.99	0.99	0.9
	Gradient Boosting	79	1835	1	0	0.99	1.00	0.99	0.9
	Decision Tree	51	1861	0	3	1.00	0.94	0.97	0.
	Random Forest	54	1861	0	0	1.00	1.00	1.00	1
	Support Vector Machine	47	1860	1	7	0.98	0.87	0.92	0.
Work	Naive Bayes	42	1860	1	12	0.98	0.78	0.87	0.
	K-Nearest Neighbors	53	1860	1	1	0.98	0.98	0.98	0.
	Gradient Boosting	53	1860	1	1	0.98	0.98	0.98	0.
	Decision Tree	48	1867	0	0	1.00	1.00	1.00	1
	Random Forest	48	1867	0	0	1.00	1.00	1.00	1
	Support Vector Machine	40	1866	1	48	0.00	0.00	0.00	0.
Bed_to_Toilet	Naive Bayes	48	1866	1	0	0.98	1.00	0.99	0.9
	K-Nearest Neighbors	48	1865	2	0	0.96	1.00	0.98	0.9
	Gradient Boosting	48	1867	0	0	1.00	1.00	1.00	1
	Decision Tree	17	1888	7	3	0.71	0.85	0.77	0.
	Random Forest	13	1892	3	7	0.81	0.65	0.72	0.
	Support Vector Machine	0	1895	0	20	0.00	0.00	0.00	0.
Wash_Dishes	Naive Bayes	14	1782	113	6	0.11	0.70	0.19	0.
	K-Nearest Neighbors	0	1895	0	20	0.00	0.00	0.00	0.
	Gradient Boosting	15	1895	3	20	0.83	0.00	0.00	0
	Decision Tree	15	1892	1	5	0.83	0.75	0.63	0.
	Random Forest	8	1904	0	2	1.00	0.50	0.63	0.
	Support Vector Machine	4	1905	0	6	1.00	0.80	0.57	0.
Housekeeping	Naive Bayes	8	1905	10	2	0.44	0.40	0.57	0.9
	K-Nearest Neighbors	7	1895	10	2	1.00	0.80	0.82	0.1
	K-Nearest Neighbors Gradient Boosting	9	1905			1.00	0.70	0.82	0.0
				1	1				

			TN	FP	FN	Precision	Recall	F1-Score	MCC
	Decision Tree	919	1037	12	2	0.99	1.00	0.99	0
	Random Forest	919	1043	6	2	0.99	1.00	1.00	(
Balan	Support Vector Machine	920	1038	11	1	0.99	1.00	0.99	(
Relax	Naive Bayes	300	1030	19	621	0.94	0.33	0.48	(
Activity Relax Relax Meal_Preparation Leave_Home Enter_Home Sleeping Eating Work	K-Nearest Neighbors	920	1039	10	1	0.99	1.00	0.99	(
	Gradient Boosting	921	1034	15	0	0.98	1.00	0.99	(
	Dedsion Tree	504	1449	6	11	0.99	0.98	0.98	(
	Random Forest	515	1439	16	0	0.97	1.00	0.98	(
	Support Vector Machine	507	1441	14	8	0.97	0.98	0.98	(
weal_preparation	Naive Bayes	123	1269	186	392	0.40	0.24	0.30	(
	K-Nearest Neighbors	508	1443	12	7	0.98	0.99	0.98	
	Gradient Boosting	501	1452	3	14	0.99	0.97	0.98	
	Decision Tree	60	1829	41	40	0.59	0.60	0.60	
	Random Forest	71	1832	38	29	0.65	0.71	0.68	(
	Support Vector Machine	98	1712	158	2	0.38	0.98	0.55	(
Leave_Home	Naive Bayes	40	1841	29	60	0.58	0.40	0.47	(
	K-Nearest Neighbors	66	1826	44	34	0.60	0.66	0.63	(
	Gradient Boosting	60	1835	35	40	0.63	0.60	0.62	
	Decision Tree	60	1830	40	40	0.60	0.60	0.60	
	Random Forest	62	1841	29	38	0.68	0.62	0.65	
	Support Vector Machine	8	1868	2	92	0.80	0.08	0.15	
Enter_Home	Naive Bayes	33	1851	19	67	0.63	0.33	0.43	
	K-Nearest Neighbors	56	1836	34	44	0.62	0.56	0.59	
	Gradient Boosting	67	1830	40	33	0.63	0.67	0.65	
	Decision Tree	150	1817	0	3	1.00	0.98	0.99	
	Random Forest	152	1816	1	1	0.99	0.99	0.99	
	Support Vector Machine	102	1817	0	6	1.00	0.96	0.98	
Sleeping	Naive Bayes	145	1778	39	8	0.79	0.95	0.86	
	K-Nearest Neighbors	145	1817	0	2	1.00	0.99	0.99	
	Gradient Boosting	152	1817	0	1	1.00	0.99	1.00	
	Decision Tree	59	1903	2	6	0.97	0.91	0.94	
	Random Forest	59	1903	1	6	0.98	0.91	0.94	
	Support Vector Machine	58	1905	0	7	1.00	0.89	0.94	
Eating	Naive Bayes	22	1357	548	43	0.04	0.34	0.07	
	K-Nearest Neighbors	62	1903	2		0.97	0.95	0.96	
	Gradient Boosting	63	1905	0	2	1.00	0.97	0.90	
	Decision Tree	50	1918	2	0	0.96	1.00	0.98	
	Random Forest	49	1918	2	1	0.96	0.98	0.98	
	Support Vector Machine	43	1918	1	1	0.98	0.84	0.97	
Work				6	20				
	Naive Bayes K-Nearest Neighbors	30 50	1914 1918	2	20	0.83	0.60	0.70	
		49	1918	2	1	0.96	0.98	0.98	
	Gradient Boosting	49			-				
	Decision Tree		1925	0	1	1.00	0.98	0.99	
	Random Forest	44	1925	0	1	1.00	0.98	0.99	
Bed_to_Toilet	Support Vector Machine	0	1924	1	45	0.00	0.00	0.00	
	Naive Bayes	18	1925	0	27	1.00	0.40	0.57	
	K-Nearest Neighbors	45	1922	3	0	0.94	1.00	0.97	
	Gradient Boosting	44	1925	0	1	1.00	0.98	0.99	
	Decision Tree	13	1954	2	1	0.87	0.93	0.90	
	Random Forest	2	1956	0	12	1.00	0.14	0.25	
wash_Disnes	Support Vector Machine	0	1956	0	14	0.00	0.00	0.00	
	Naive Bayes	2	1799	157	12	0.01	0.14	0.02	
	K-Nearest Neighbors	2	1956	0	12	1.00	0.14	0.25	
	Gradient Boosting	12	1956	0	2	1.00	0.86	0.92	
	Decision Tree	5	1964	1	0	0.83	1.00	0.91	
	Random Forest	4	1965	0	1	1.00	0.80	0.89	
Housekeeping	Support Vector Machine	3	1965	0	2	1.00	0.60	0.75	
Housekeening			1714	251	2	0.01	0.60	0.02	
Housekeeping	Naive Bayes K-Nearest Neighbors	3	1714 1964	1	3	0.67	0.40	0.50	

11th MALAYSIA STATISTICS CONFERENCE







- Best-recognized activities: Relax, Meal Preparation, Sleeping, Eating, Work, Bed to Toilet.
- Time-related features improved recognition of time-specific activities like Sleeping and Eating.
- Challenges with recognizing activities like Wash Dishes and Housekeeping.

11Th MALAYSIA STATISTICS CONFERENCE

FINDINGS

FUTURE WORK

Tree-based methods excelled in handling behavioral variability. Time-related features offered modest improvements.

SVM's rigid boundaries didn't handle overlapping activities well.

03

Naive Bayes struggled with feature independence assumptions.

11Th MALAYSIA STATISTICS CONFERENCE "Data and Artificial Intelligence: Empowering the Future"

02

OBJECTIVE | METHODOLOGY | ALGORITHM PERFORMANCE | FINDINGS



Tree-based methods effectively classify ADLs in smart homes.

FUTURE WORK

- Future research should focus on similar activity recognition and advanced feature engineering.
- Real-world application in Malaysian smart homes.

11Th MALAYSIA STATISTICS CONFERENCE

References

1. Choi, M., Sempungu, J. K., Lee, E. H., & Lee, Y. H. (2024). Living longer but in poor health: Healthcare system responses to ageing populations in industrialised countries based on the findings from the global burden of disease study 2019. BMC Public Health, 24(1). https://doi.org/10.1186/s12889-024-18049-0

2. Cook, D. (2012). Learning setting-generalized activity models for smart spaces. IEEE Intelligent Systems, 27(1), 32–38. https://doi.org/10.1109/mis.2010.112

3. Department of Statistics Malaysia (DOSM, 2016). Population Projection (Revised), Malaysia, 2010-2040. Retrieved July 7, 2024, from https://www.dosm.gov.my/portalmain/release-content/population-projection-revised-malaysia-2010-2040.

4. Facchinetti, G., Petrucci, G., Albanesi, B., De Marinis, M. G., & Piredda, M. (2023). Can smart home technologies help older adults manage their chronic condition? A systematic literature review. International Journal of Environmental Research and Public Health, 20(2), 1205. https://doi.org/10.3390/ijerph20021205

5. Lai, W.-H., Hon, Y.-K., Pang, G. M.-H., Chong, E. M.-G., Nordin, N., Tiong, L.-L., Tan, S. H., Sapian, R. A., Lee, Y.-F., & Rosli, N. (2022). Dementia of the ageing population in Malaysia: A scoping review of published research. Aging and Health Research, 2(2), 100077. https://doi.org/10.1016/j.ahr.2022.100077

6. Nižetić, S., Šolić, P., López-de-Ipiña González-de-Artaza, D., & Patrono, L. (2020). Internet of things (IOT): Opportunities, issues and challenges towards a smart and sustainable future. Journal of Cleaner Production, 274, 122877. https://doi.org/10.1016/j.jclepro.2020.122877

7. United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP, 2023). "Malaysia | Demographic Changes." UNESCAP, Retrieved July 7, 2024 from https://www.population-trends-asiapacific.org/data/MYS.

8. World Health Organization. (2020). Supporting people living with dementia in Malaysia. Retrieved July 23, 2024, from https://www.who.int/westernpacific/news-room/feature-stories/item/support

Thank You!

11Th MALAYSIA STATISTICS CONFERENCE