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Frailty Screening for Community-dwelling Older Adults in Northern Thailand using Machine Learning Models

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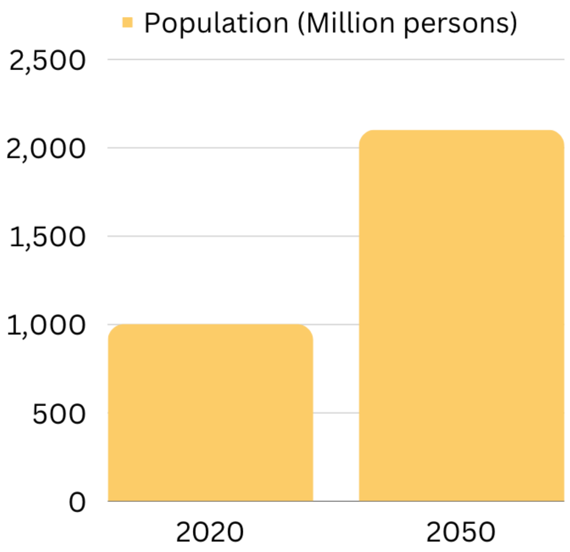
What is Frailty?

A clinical state of increased vulnerability due to age-associated decline of an individual’s body resulting in increased morbidity and mortality when exposed to everyday or acute stressor.

Why focus on frailty?

The number of people aged 80 years old and older will reach

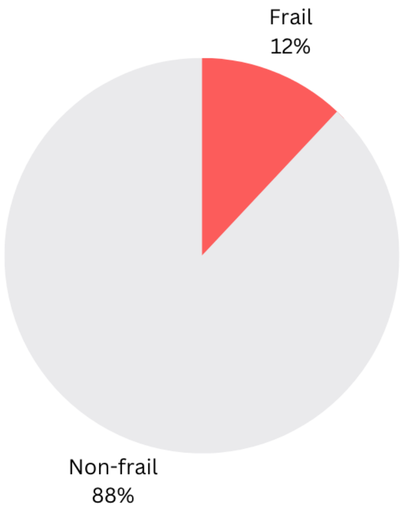
426 million in 2050 (2)



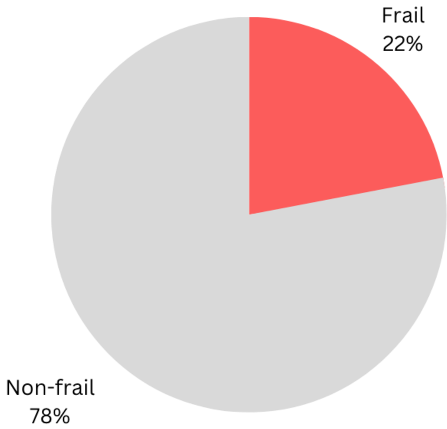
According to WHO the population aged 60 years and over will increase from 1 billion in 2020 to 2.1 billion in 2050 (1)

1. World population ageing, 2019 : highlights. 2019; Available from: http://digitallibrary.un.org/record/3846855
2. Ageing and health [Internet]. [cited 2022 Aug 2]. Available from: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health

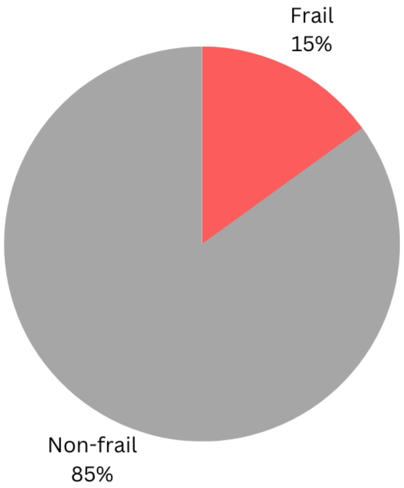
Why focus on frailty?



Global Frailty Prevalence (3)



Thai Frailty Prevalence



Thai Northern Region Frailty Prevalence (4)

3. O'Caoimh R, Sezgin D, O'Donovan MR, Molloy DW, Clegg A, Rockwood K, et al. Prevalence of frailty in 62 countries across the world: a systematic review and meta-analysis of population-level studies. Age Ageing. 2021 Jan 8;50(1):96–104.
4. Srinonprasert V, Chalermsri C, Aekplakorn W. Frailty index to predict all-cause mortality in Thai community-dwelling older population: A result from a National Health Examination Survey cohort. Arch Gerontol Geriatr. 2018 Jul;77:124–8.

Why focus on frailty?

- Decreased quality of life
- Decreased strength
- Increased risk of fall
- Increased re-admission hospitalization
- Increased all-cause mortality
- Slow gait speed
- Depressive symptoms (5,6,7,8)

5. Nguyen, Nguyen, Nguyen, Nguyen, Nguyen, Pham, et al. Frailty Prevalence and Association with Health-Related Quality of Life Impairment among Rural Community-Dwelling Older Adults in Vietnam. Int J Environ Res Public Health. 2019 Oct 12;16(20):3869.
6. Setiati S, Laksmi PW, Aryana IGPS, Sunarti S, Widajanti N, Dwipa L, et al. Frailty state among Indonesian elderly: prevalence, associated factors, and frailty state transition. BMC Geriatr. 2019 Dec;19(1):182.
7. Srinonprasert V, Chalermsri C, Aekplakorn W. Frailty index to predict all-cause mortality in Thai community-dwelling older population: A result from a National Health Examination Survey cohort. Arch Gerontol Geriatr. 2018 Jul;77:124–8.
8. Cheng MH, Chang SF. Frailty as a Risk Factor for Falls Among Community Dwelling People: Evidence From a Meta-Analysis: Falls With Frailty. J Nurs Scholarsh. 2017 Sep;49(5):529–36.

FRAILTY could be reversed.

EARLY DETECTION

EXERCISE INTERVENTION

NUTRITION INTERVENTION

9. Travers J, Romero-Ortuno R, Bailey J, Cooney MT. Delaying and reversing frailty: a systematic review of primary care interventions. Br J Gen Pract. 2019 Jan;69(678):e61–9.
10. Bray NW, Smart RR, Jakobi JM, Jones GR. Exercise prescription to reverse frailty. Appl Physiol Nutr Metab. 2016 Oct;41(10):1112–6.
11. Marcucci M, Damanti S, Germini F, Apostolo J, Bobrowicz-Campos E, Gwyther H, et al. Interventions to prevent, delay or reverse frailty in older people: a journey towards clinical guidelines. BMC Med. 2019 Dec;17(1):193.

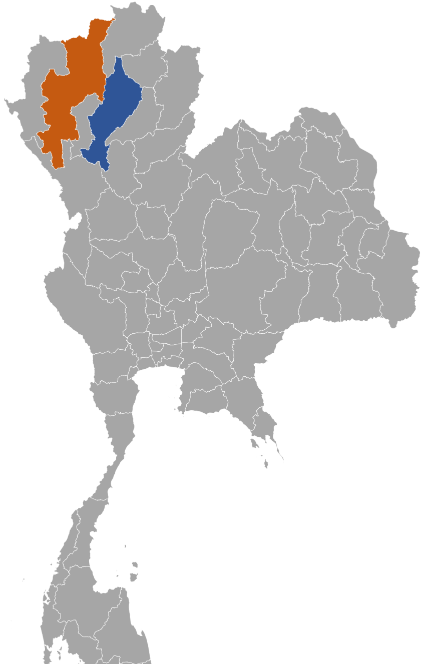
Research Question

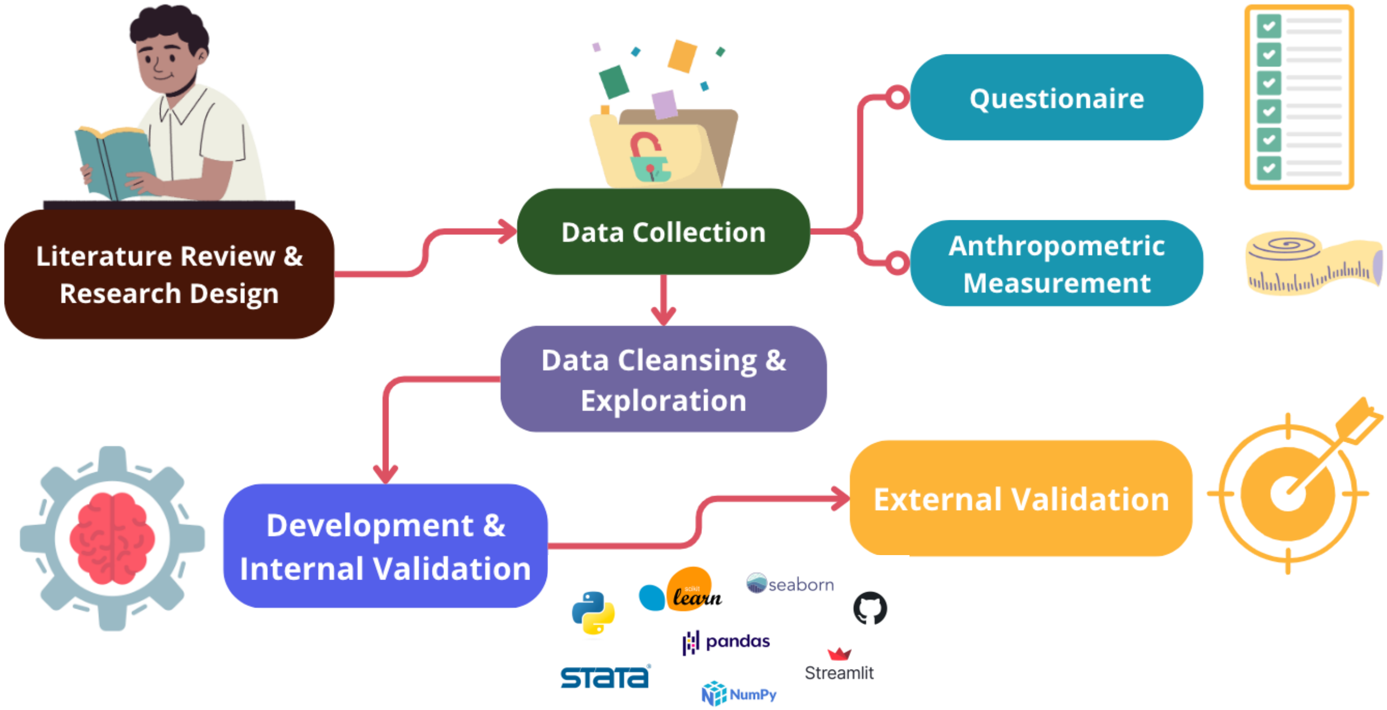
Can machine learning models screen frailty in community-dwelling older adults in Northern Thailand?

Research Objectives

- To develop and internally validate performance of frailty prediction using machine learning models in community-dwelling older adults in Lampang, Thailand
- To externally validate machine learning models in community-dwelling older adults in Chiang Mai, Thailand

Methods

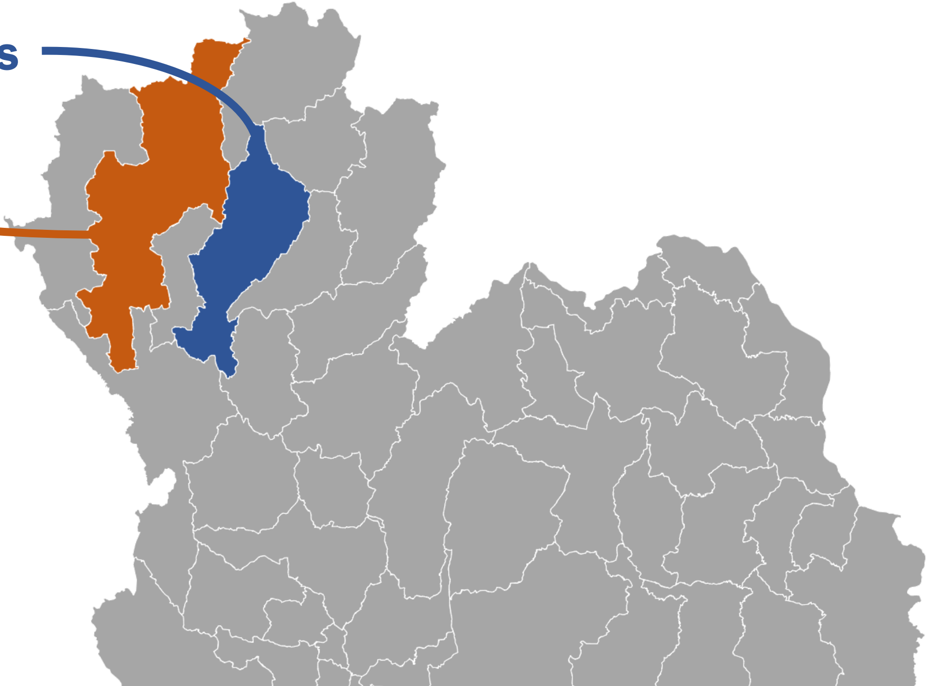



Literature Review & Research Design
Data Collection
Questionaire
Anthropometric Measurement
Data Cleansing & Exploration
Development & Internal Validation
External Validation
seaborn
learn
pandas
Streamlit
STATA
NumPy

Methods: Source of Data

Development & Internal Validation Datasets
Lampang, Thailand: 2,228 Samples

External Validation Datasets
Chiang Mai, Thailand: 464 Samples



- Old adults aged 60 years and above.
- Cross-sectional Survey
- Those with dementia (as determined by the Thai Mental State Examination), blindness, deafness, **bedridden** status, disabilities, or severe acute diseases will be excluded.

Predictors: Characteristics and Demographics

- Socio-demographic (age, living status, gender, and education level)
- Self-reported medical diagnoses (such as hypertension, diabetes mellitus, and heart disease)
- Level of physical activity per week
- Level of Exhaustion

Predictors: Anthropometric Variables

- Body mass index
    - Height
    - Bodyweight
- Circumference of waist and calves
- Handgrip strength
- Walking time

Data Exploration

Table 1. The characteristics of participants in the development and internal validation datasets, and the external validation dataset.

Characteristics	Development and internal validation datasets (Lampang, 2016-2017) (N = 2,228)	External validation datasets (Chiang Mai, 2021) (N = 464)	*p*-value
	***n* (%)**	***n* (%)**	
Age (years), mean (±SD)	70.96 (±7.49)	70.68 (±5.58)	0.446
Gender			
Male	1,569 (70.45%)	193 (41.59%)	<0.001
Female	658 (29.55%)	271 (58.41%)	
Status			
Living alone	160 (7.18%)	42 (9.05%)	<0.001
Living with spouse	1,177 (52.85%)	9 (1.94%)	
Living with children	823 (36.96%)	283 (60.99%)	
Living with Relatives or others	67 (3.01%)	130 (28.02%)	
BMI (kg./m²), mean (±SD)	32.64 (±7.40)	22.73 (±3.89)	0.001
Education			
No Education	192 (8.62%)	12 (2.61%)	<0.001
Primary School	1,745 (78.36%)	398 (86.52%)	
Secondary School or Higher	290 (13.02%)	50 (10.87%)	
Underlying diseases			
Hypertension	1,008 (45.26%)	237 (51.08%)	0.022
Dyslipidaemia	438 (19.67%)	79 (17.03%)	0.190
Type 2 Diabetes Mellitus	361 (16.21%)	78 (16.81%)	0.747
Heart diseases	96 (4.31%)	18 (3.88%)	0.676
Anthropometric variables			
Waist Circumference (cm), means (±SD)	83.40 (±11.23)	81.16 (±10.80)	<0.001
Calf Circumference (cm), means (±SD)	32.40 (±4.35)	32.85 (±4.55)	0.044
Walk time (min), means (±SD)	6.42 (±2.01)	8.50 (±5.38)	<0.001
Exhaustion	218 (9.79%)	189 (40.74%)	<0.001
Adequate level of Physical Activity by WHO	363 (16.30%)	104 (22.42%)	<0.001
Grip Strength (kg), means (±SD)	32.40 (±6.68)	19.87 (±7.29)	<0.001

Features Selection

Table 2. The comparison of participants' characteristics and their associations with frailty in the development and internal validation datasets.

Characteristics	Frailty (*n* = 385) *n* (%)	Non-frailty (*n* = 1842) *n* (%)	Crude aOR (95% CI)	*p*-value
Age (years), mean (±SD)	69.87 (±6.99)	385 (±7.60)	1.12 (1.10-1.14)	< 0.001
Gender				
Female	105 (27.27%)	553 (30.02%)	(ref.)	
Male	280 (72.73%)	1289 (69.98%)	0.87 (0.68-1.11)	0.283
Status				
Living alone	22 (5.71%)	138 (7.49%)	(ref.)	
Living with spouse	159 (41.30%)	1018 (55.27%)	0.98 (0.61-1.58)	0.933
Living with children	189 (49.09%)	634 (34.42%)	1.87 (1.16-3.01)	0.01
Living with Relatives or others	15 (3.90%)	52 (2.82%)	1.81 (0.87-3.75)	0.11
BMI (kg./m²), mean (±SD)	29.55 (±7.74)	33.28 (±7.16)	0.93 (0.91-0.95)	<0.001
Education				
No Education	54 (14.03%)	138 (7.49%)	(ref.)	
Primary School	289 (75.06%)	1,456 (79.04%)	0.51 (0.36-0.71)	<0.001
Secondary School or higher	42 (10.91%)	248 (13.46%)	0.43 (0.28-0.68)	<0.001
Underlying diseases				
Hypertension	201 (52.21%)	807 (43.81%)	1.40 (1.12-1.74)	0.003
Dyslipidaemia	82 (21.30%)	356 (19.33%)	1.13 (0.86-1.48)	0.376
Type 2 Diabetes Mellitus	70 (18.18%)	291 (15.80%)	1.18 (0.88-1.58)	0.248
Heart diseases	25 (6.49%)	71 (3.85%)	1.73 (1.08-2.77)	0.020
Waist Circumference (cm), means (±SD)	83.21 (±12.01)	83.43 (±11.06)	0.99 (0.99-1.01)	0.723
Calf Circumference (cm), means (±SD)	31.75 (±3.94)	32.54 (±4.42)	0.95 (0.92-0.98)	0.001
Walk time (min), means (±SD)	8.55 (±2.6)	5.97 (±1.52)	2.04 (1.88-2.20)	< 0.001
Exhaustion	153 (39.74%)	65 (3.53%)	18.03 (13.08-24.85)	< 0.001
Adequate level of Physical Activity by WHO	148 (38.44%)	215 (11.67%)	4.73 (3.68-6.07)	< 0.001
Grip Strength (kg), means (±SD)	14.42 (±3.99)	20.74 (±6.62)	0.81 (0.78-0.83)	< 0.001

Model Development & Internal Validation

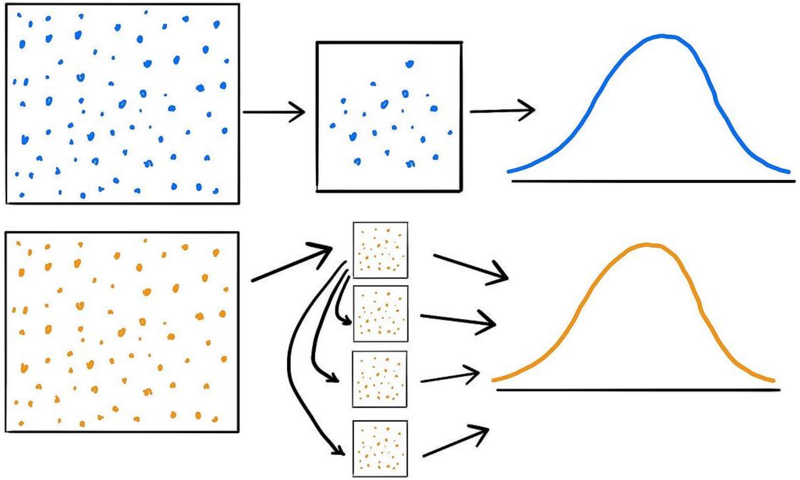
- Resolved unbalanced classification for the dataset's minority class by employing the Synthetic Minority Oversampling Technique (SMOTE) to enhance model decision boundaries via imblearn.over_sampling.SMOTE package

Model Development & Internal Validation

- K-Nearest Neighbors (KNN) algorithm, Random Forest ML algorithms (RF), Multi-layer Perceptron Artificial Neural Network (MLP), Gradient Boosting Classifier (GBC), Linear Support Vector Classifier (SVM) and Logistic Regression (LR) models via the Scikit-Learn library 1.1.2.
- The hyperparameters will be determined by using a grid search via the GridSearch CV package with 10-fold cross-validation

External Validation

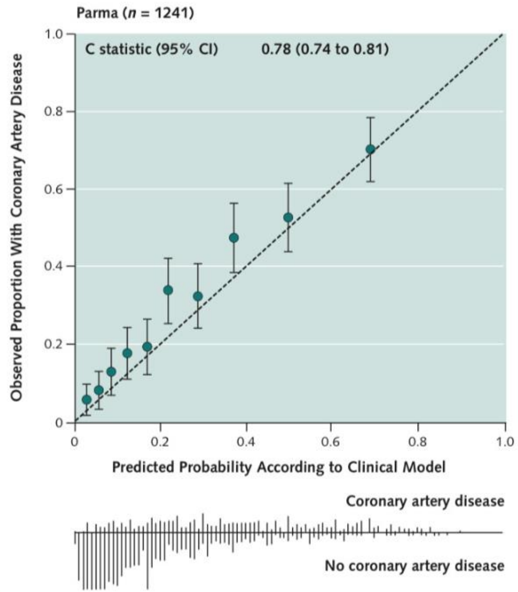
- Discriminative performance matrices and a 95%CI of AUC from the 1000-bootstrapping samples.



Model Calibration

- To ensure that the estimated class probabilities are consistent with what would naturally occur.

Figure 8. Example figure: a calibration plot with c-statistic and distribution of the predicted probabilities for individuals with and without the outcome (coronary artery disease).



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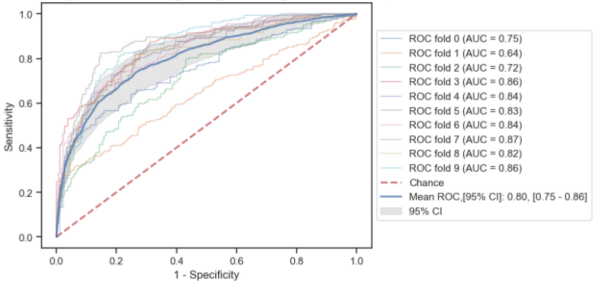
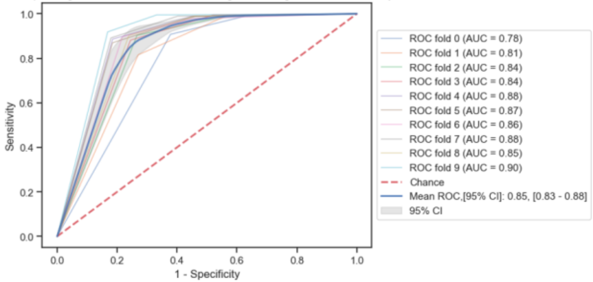
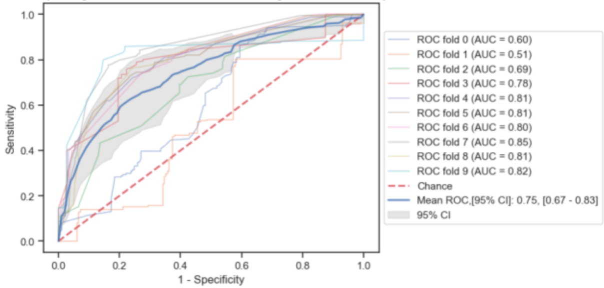
Receiver Operating Characteristic of Logistic Regression using Rebalanced Data by SMOTE



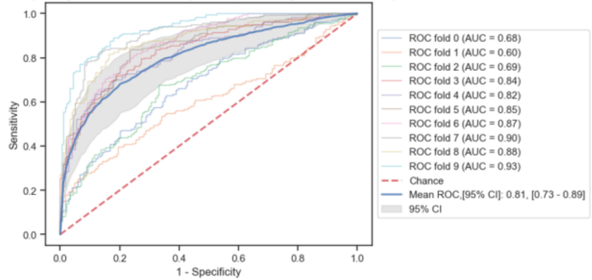
Receiver Operating Characteristic of K-nearest Neighbors using Rebalanced Data by SMOTE



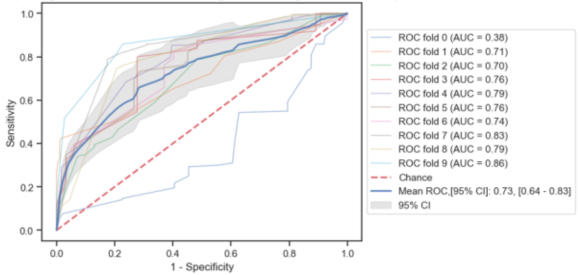
Receiver Operating Characteristic of Random Forest using Rebalanced Data by SMOTE



Receiver Operating Characteristic of Multilayer Perceptrons using Rebalanced Data by SMOTE



Receiver Operating Characteristic of Gradient Boosting Classifier using Rebalanced Data by SMOTE



Receiver Operating Characteristic of Linear Support Vector Classifier using Rebalanced Data by SMOTE

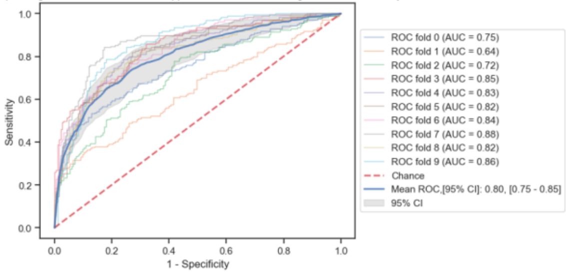


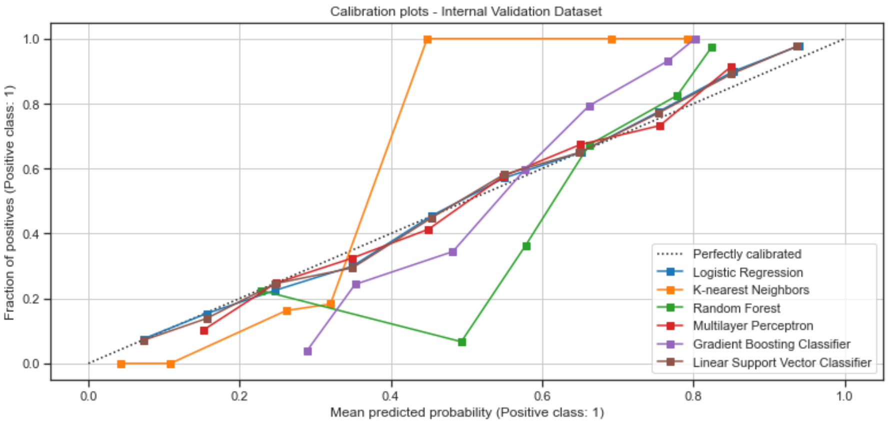
Table 3. Discrimination and Optimism of Internal Validated models.

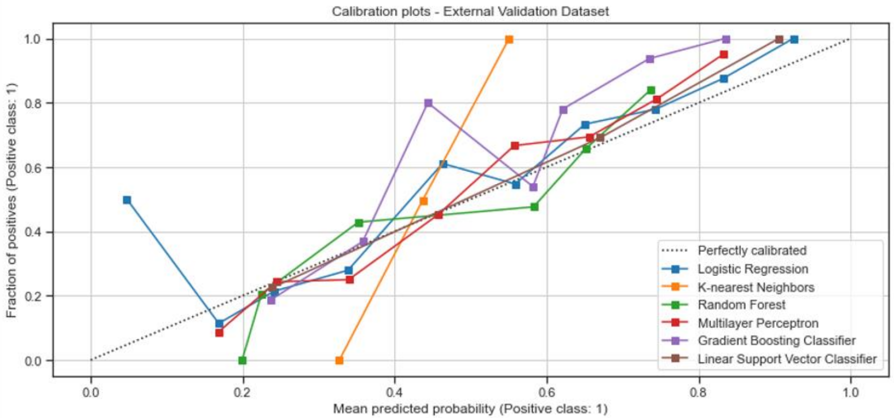
Models	Model prediction	(Frailty/ Non-frailty)	AUC		Predictive values		Sensitivity	Specificity
			mean	95% CI	Positive	Negative		
LR	Frailty	1349/493	0.80	(0.75 - 0.86)	0.73	0.73	0.73	0.73
	Non-frailty	504/1338						
KNN	Frailty	1634/208	0.85	(0.83 - 0.88)	0.79	0.87	0.89	0.77
	Non-frailty	430/1412						
RF	Frailty	1491/351	0.75	(0.67 - 0.83)	0.66	0.75	0.81	0.58
	Non-frailty	773/1069						
MLP	Frailty	1373/469	0.81	(0.73 - 0.89)	0.71	0.73	0.75	0.70
	Non-frailty	522/1320						
GBC	Frailty	1372/470	0.73	(0.64 - 0.83)	0.66	0.70	0.73	0.63
	Non-frailty	639/1203						
SVM	Frailty	1349/493	0.80	(0.75 – 0.85)	0.72	0.71	0.71	0.72
	Non-frailty	506/1336						

Table 4. Discrimination and Optimism of External validated models.

Models	Model prediction	(Frailty/ Non-frailty)	AUC		Predictive values		Sensitivity	Specificity
			mean	95% CI	Positive	Negative		
LR	Frailty	141/51	0.75	(0.71 - 0.78)	0.68	0.73	0.73	0.76
	Non-frailty	65/203						
KNN	Frailty	39/153	0.54	(0.51 - 0.57)	0.53	0.20	0.20	0.87
	Non-frailty	34/234						
RF	Frailty	135/57	0.74	(0.71 - 0.78)	0.70	0.70	0.70	0.78
	Non-frailty	59/209						
MLP	Frailty	42/150	0.54	(0.51 - 0.57)	0.53	0.22	0.22	0.86
	Non-frailty	37/231						
GBC	Frailty	61/131	0.60	(0.57 – 0.63)	0.68	0.32	0.32	0.65
	Non-frailty	29/239						
SVM	Frailty	131/61	0.73	(0.70 – 0.77)	0.69	0.68	0.68	0.78
	Non-frailty	58/210						

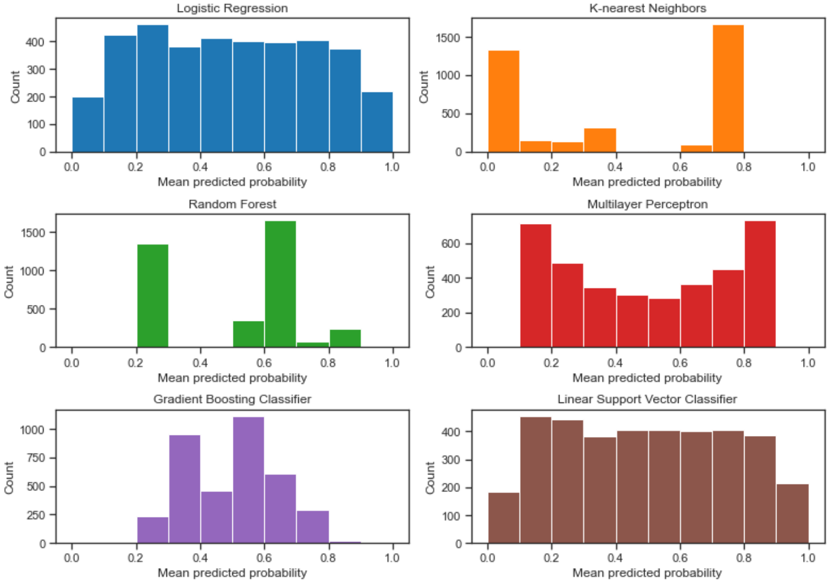
Model Calibration Results



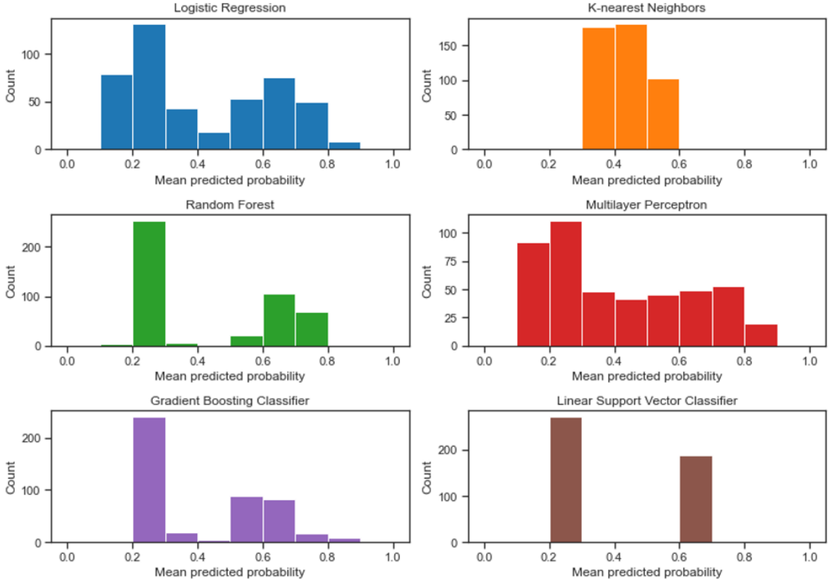


Model Calibration Results

Internal Validated Models



External Validated Models

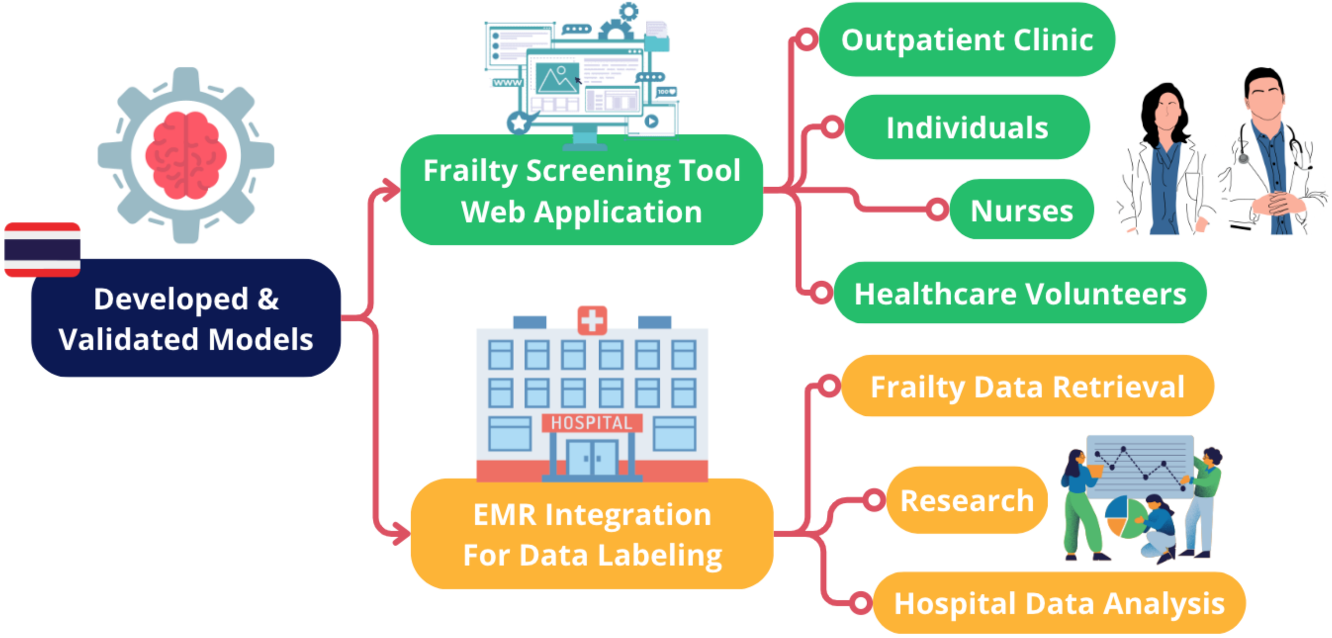


Research Question

Can machine learning models screen frailty in community-dwelling older adults in Northern Thailand?

Absolutely!

Models Implication



Criteria Used to Define Frailty

- **Weight loss:** "In the last year, have you lost more than 10 pounds unintentionally (i.e., not due to dieting or exercise)?" If yes, then frail for weight loss criterion. At follow-up, weight loss was calculated as: (Weight in previous year – current measured weight)/(weight in previous year) = K. If K ≥ 0.05 and the subject does not report that he/she was trying to lose weight (i.e., unintentional weight loss of at least 5% of previous year's body weight), then frail for weight loss = Yes.
- **Exhaustion:** Using the CES–D Depression Scale, the following two statements are read. (a) I felt that everything I did was an effort; (b) I could not get going. The question is asked "How often in the last week did you feel this way?" 0 = rarely or none of the time (<1 day), 1 = some or a little of the time (1–2 days), 2 = a moderate amount of the time (3–4 days), or 3 = most of the time. Subjects answering "2" or "3" to either of these questions are categorized as frail by the exhaustion criterion.
- **Physical Activity:** Based on the short version of the Minnesota Leisure Time Activity questionnaire, asking about walking, chores (moderately strenuous), mowing the lawn, raking, gardening, hiking, jogging, biking, exercise cycling, dancing, aerobics, bowling, golf, singles tennis, doubles tennis, racquetball, calisthenics, swimming. Kcals per week expended are calculated using standardized algorithm. This variable is stratified by gender.

  Men: Those with Kcals of physical activity per week <383 are frail.

  Women: Those with Kcals per week <270 are frail.

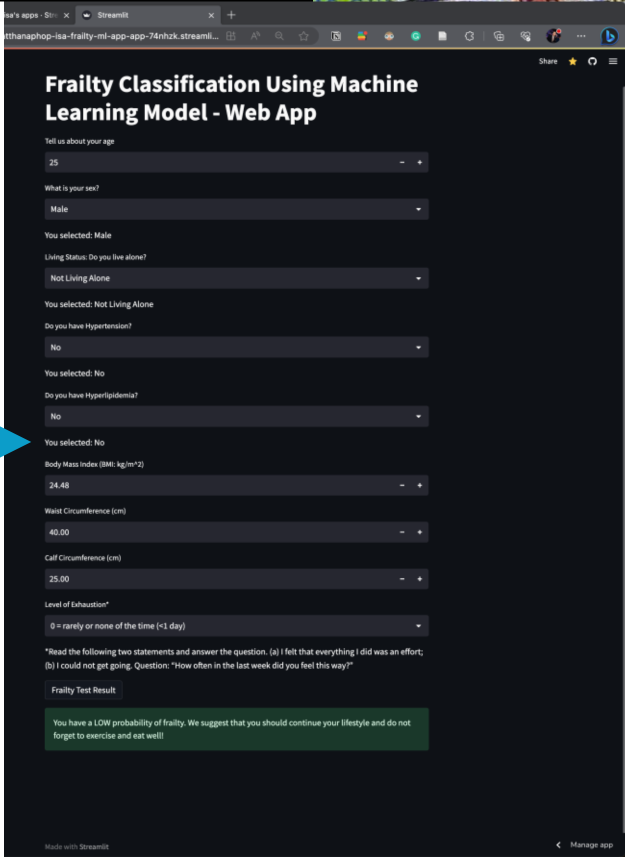
- **Walk Time**, stratified by gender and height (gender-specific cutoff a medium height).

Men	*Cutoff for Time to Walk 15 feet criterion for frailty*
Height ≤ 173 cm	≥7 seconds
Height > 173 cm	≥6 seconds
Women	
Height ≤ 159 cm	≥7 seconds
Height > 159 cm	≥6 seconds

- **Grip Strength**, stratified by gender and body mass index (BMI) quartiles:

Men	*Cutoff for grip strength (Kg) criterion for frailty*
BMI ≤ 24	≤29
BMI 24.1–26	≤30
BMI 26.1–28	≤30
BMI > 28	≤32
Women	
BMI ≤ 23	≤17
BMI 23.1–26	≤17.3
BMI 26.1–29	≤18
BMI > 29	≤21

Try the app!



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Current Project in collaboration with Medical University of Graz, Austria: **Development and validation of clinical document normalization using pre-trained deep learning models in discharge summary notes from a Thai tertiary care hospital**

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